
# Sensing – New Insights into Grassland Science and Practice

*Edited by*

**T. Astor**
**I. Dzene**


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T. Astor
I. Dzene

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European Grassland Federation EGF
W. Kessler, Federation Secretary
c/o Agroscope
Reckenholzstrasse 191
8046 Zurich, Switzerland
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## Foreword

The 21st symposium of the European Grassland Federation is hosted by Germany. Twenty-five years ago the Universities of Göttingen and Kassel jointly hosted an EGF symposium on the topic of Organic Grassland Farming. During the past quarter-century grassland science and management have changed greatly. In the search for more sustainable grassland production, research has generated an immense body of knowledge on all aspects of this complex soil-plant-animal system. New technologies have emerged, providing detailed information on a variety of grassland traits; for instance, biomass, quality and botanical composition. Remotely sensed information was barely available 25 years ago. Only during the last 5 to 10 years have platforms, sensors and algorithms become widely available and with sufficient temporal and spatial resolutions relevant for applications to practical grassland farming.

This aims of this symposium are to bring together the existing knowledge in this relatively new field of research, to feature upcoming innovations, and to identify existing limitations and challenges. A major goal is to contribute to bridging the gap between the complex and research-intensive technological processes, and the demands for feasible approaches in practical grassland farming. The meeting has three themes: (1) Biomass and quality characteristics; (2) Biodiversity and other ecosystem services; (3) Management and decision support. Sensing tools and methods assisting management and decision support in grazing and cutting regimes are introduced and evaluated in plenary and poster sessions. They cover all levels of grassland intensity: from intensive grazing systems to grasslands for nature conservation purposes.

The Covid-19 pandemic has presented an additional challenge for our symposium. We decided early on to move from a meeting in physical presence to an online-based meeting, which made it possible to develop the web-based platform with the utmost care and to design it as close as possible to a face-to-face conference.

We would like to thank all the authors for submitting such a broad range of interesting papers. We are grateful to all the reviewers and editors for providing constructive feedback. Finally, we would like to express our gratitude to all members of the local organising committee, the scientific committee, and to all the innumerable helpers for making this exciting symposium possible.

Despite the difficulties caused by the Covid-19 pandemic, we wish that the EGF symposium will provide novel insights for grassland science and management and stimulate fruitful discussions and networking.

Michael Wachendorf
*Chair of the organising committee*

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# Introduction

# Towards an informed grassland farming – Shortfalls and perspectives

Isselstein J.

*University of Göttingen, Department of Crop Sciences, Grassland Science, Von-Siebold-Str. 8, D-37075 Göttingen, Germany*

## Abstract

Grassland in Europe provides a wide range of ecosystem services. However, the extent to which these services are provided often falls short of the expectations of agriculture and society. On the one hand, the provisioning potential of individual ecosystem services is not fully exploited, on the other hand, there are strong trade-offs between different ecosystem services. One reason for unsatisfactory performance is the lack of knowledge and information on functional relationships between management measures and ecosystem function targets. As a result, management decisions are not sufficiently targeted. New technological developments in smart farming in the field of sensor technology and information processing open up a wide range of possibilities for obtaining data to document biological production processes with a high temporal and spatial resolution. The information can be used to rationalize production processes and reduce trade-offs between different services. This paper examines the weaknesses of current grassland management practices, provides a summary of technological innovations, and analyses their potential applications using pasture management as an example.

**Keywords:** smart grassland farming, technological innovations, livestock grazing, ecosystem services, managing trade-offs

## Introduction

Permanent and temporary grasslands cover some 40% of the agriculturally utilized area in Europe. Grassland systems are a major contributor to the food sector. They enable the keeping of grazing livestock, which account for about 60% of all agricultural livestock in Europe. These livestock provides 6about 25% of the food energy of the human diet (Huyghe *et al*., 2014). The grassland-based production of food thus represents an important area of the bioeconomy of the entire national economy. In the bioeconomy it is important that biological production processes can be precisely managed and controlled. Only then can the goals pursued with the production process be precisely achieved. This works well with production processes that take place under largely or completely controlled conditions. These include, for example, the horticultural production of vegetables and fruit in greenhouses or the production of processed products with the help of microorganisms, such as yoghurt and cheese, or fermented beverages. The better the chemical and biological (scientific) fundamentals of the production processes are understood, the more effectively the production process can be designed. What is true for industrial biological processes is in principle also true for agriculture and especially for grassland farming. However, grassland farming differs from industrial bioeconomy business. Grassland systems are more complex. On the one hand, they are closer to nature and thus more dependent on environmental factors that can hardly be controlled. On the other hand, there are more products/services being produced, not only the livestock produce. Rather, diverse services are provided, each of which can be highly variable within the category. This applies to food as well as to environmental services. In addition, many sequential production steps are required and different components are involved. A grassland-based production system includes the soil-dependent production of fodder and the livestock production that converts the fodder into high-quality food. Controlling such a production system is obviously difficult. Rational management decisions require that the effects of these decisions can be predicted as precisely as possible. Practical experience plays an important role here, but the considerable progress in production in recent decades has been achieved through scientific knowledge about the principles of production processes (see Caradus, 2006; Lemaire *et al*., 2005). Despite these advances in grassland farming, production processes are not optimized, the forage production potential of a site is not achieved and the efficiency of conversion of plant energy into livestock energy is unsatisfactory (Huson *et al*., 2020; McConnell *et al*., 2020). In addition, there are major uncertainties with regard to the provision of environmental services. This is obviously due to a lack of information or accessibility of information for stakeholders. The aim of the present paper is to analyse (i) to what extent

there is a lack of accessible information for rational grassland management in the farming practice, (ii) which areas of grassland management are particularly affected by this, (iii) which technological developments could remedy the information deficit, and (iv) how technological developments can be applied successfully in production processes.

## Challenges for grassland farming

Grasslands in Europe are extremely diverse and they support a variety of important ecosystem services apart from milk and meat (Peeters and Isselstein, 2019). The vast majority of European grasslands are man-made habitats. Their diversity is a result of a broad range of different site and environmental conditions interacting with a large variety of farming measures (Dengler, 2014; Poschlod, 2017). A continuous management is thus required to maintain the diversity of ecosystem services. The provision of such a diversity of ecosystem services has been summarized by the term 'multifunction grassland' and this term has received increasing attention in science, and also in society and politics in recent decades (e.g. Lemaire *et al*., 2005, Isselstein and Kayser, 2014; Huguenin-Elie *et al*., 2018). The conceptual idea behind the term multifunction grassland is that different grassland management objectives can be achieved simultaneously. A single objective should not be given priority at the expense of one or more other objectives. For decades, however, this was the case. Production goals were expanded at the expense of the environment. In many cases, grassland farming was intensified in order to produce more fodder per hectare and to achieve higher livestock yields. This provoked environmentally harmful emissions and reduced biodiversity.

Table 1. Simplified representation of the site and management conditions under which high or maximum performance is achieved for the various ecosystem services (own compilation).

| Ecosystem service | **Food**: produce feed and food | **Nature**: protect and promote biodiversity | **Climate**: reduce greenhouse gas emissions, sequester carbon | **Water**: provide sufficient and clean water | **Culture**: preserve typical cultural landscapes |
|---|---|---|---|---|---|
| Domain/ Characteristic | | | | | |
| site/soil | fertile, well supplied with basic nutrients | rather low fertility, low in basic nutrients | no tillage and sward disturbance | rather low fertility, high water permeability | small paddocks, diverse landscape structure. |
| soil water availability | moderate, no surplus, no drought | either dry or wet sites | wet on organic soils | no clear effect | diverse, from low to high |
| herbage quantity | Moderate | rather low | rather high | rather low for high water quantity, rather high for high water quality. | diverse, from low to high |
| herbage quality | High | often low, mature herbage | high to reduce methane emission by ruminants, low crude protein content to reduce $N_2O$ emissions | low to moderate | diverse, from low to high |
| Fertilization | moderate to high | none to low | none to low | low to moderate | rather low |
| Defoliation | Frequent | infrequent | depending on methane or $N_2O$ emission, either infrequent or frequent | rather frequent | diverse, grazing, mowing, frequent, infrequent |

The question is: what causes such trade-offs, and are they are unavoidable? In order to answer this question, we will first describe the conditions under which particularly high performance is achieved in

individual ecosystem services, without taking trade-offs into account. Table 1 provides a simplified, cursory summary of the site and management conditions under which high or maximum performance is expected in the individual areas of ecosystem services. With regard to production, it is well researched and known in the farming practice which conditions lead to high performance: amelioration of the soil conditions, i.e. a reasonable supply of basic nutrients and moderate conditions of soil water relations, swards dominated by efficient forage plant species and varieties, nutrient replacement through fertilization, and intensive grassland use. For other ecosystem services, knowledge is much less and is less specific. This leads to uncertainties in accurately assessing the consequences of management measures. In addition, interactions between management measures and site factors complicate the assessment of ecosystem services. In Table 1, this is reflected in the fact that maximum performance of environment-related ecosystem services can be achieved with different constellations of environmental factors.

The key challenge for grassland farming is to design the livestock production system and management measures in such a way that the multiple functions and services are adequately fulfilled or provided. As Table 1 shows, this is not fully possible because the environmental and management conditions that lead to high performance vary by ecosystem service. There are trade-offs between the different ecosystem services and their extent depends on the site/environment and management conditions. A broad study by Le Clec'h *et al*. (2019) found that, in general, extensive management tends to favour environmental services at the expense of production services and, conversely, that intensive systems tend to facilitate production services at the expense of environmental services. However, the aim of targeted grassland management must be to reduce trade-offs and to bring the different goals of grassland management more in line with each other. Obviously, however, there is a lack of knowledge in this regard.

## Information gaps leading to inefficiencies of grassland farming

Grassland management is integrated into a value chain and must take into account the demands of society with regard to services of general interest. The socio-economic and societal framework conditions shape the production goals and the scope of action for grassland management. Inefficiencies in grassland management and unsatisfactory ecosystem services can be attributed to a relevant extent to information deficits. These information gaps exist at all levels of agriculture and the socio-economic framework. Accordingly, it is not only the grassland farmers who are affected by information gaps in their production decisions, but also the extension services, the agricultural authorities that implement the European Agricultural Policy and establish agri-environment programmes, the environmental authorities that are responsible for compliance with environmental standards and the elements of the downstream value chain that process and market agricultural products.

In the following, examples of information deficits that lead to inefficiencies in grassland management and the achievement of comprehensive ecosystem services are highlighted.

Production: Information deficits concern decisions on the livestock production system, the type of grassland utilization (cutting, grazing, forage conservation, fresh grass), the grazing system or cutting date and frequency, forage species and variety selection and fertilization. With regard to forage production, the production potential is often not reached; there is a yield gap (Schils *et al*., 2018). In addition, grass utilization by the grazing livestock is not efficient, i.e. the herbage energy is insufficiently converted into animal output, and there are herbage losses. This is due to a lack of knowledge about the site-specific yield effects of management measures. Information with a high temporal resolution on herbage mass and growth rate, herbage quality, i.e. nutrient and energy concentration and their metabolizability, the botanical composition of the sward, i.e. the proportion of valuable forage species and weeds, the proportion of legumes and the estimation of biological N fixation, or the occurrence of plant diseases (van den Pol-van Dasselaar *et al*., 2020; Aubry *et al*., 2020; McConnell *et al*., 2020; Huson *et al*., 2020).

Services for public goods: These include services provided by grassland that are not rewarded through market mechanisms, but which are increasingly desired by society. These are services for environmental protection, biodiversity, water pollution control or the preservation of the cultural landscape. As these services have not been given priority attention by farmers for a long time, there are

considerable information gaps with regard to the efficient provision of such services. This concerns the choice of appropriate management measures for the conservation and promotion of rare species such as high nature value plant species, meadow birds, grasshoppers or butterflies. Likewise, there are uncertainties in estimating the impact of management measures on the targeted promotion of biodiversity on species-poor grassland, the avoidance of greenhouse gas emissions without significantly reducing production performance, the increase of carbon sequestration of grassland systems or the avoidance of nitrate leaching. There are also problems with the evaluation, control and appropriate remuneration of public goods.

In order to close information gaps, efforts are required at various levels. Research and development have made considerable technological progress in various areas of information acquisition and processing in recent years, the widespread use of which in the further development of grassland-based production systems and implementation in grassland farming practice is still largely pending.

## Technological innovation with a potential to improve grassland management information

Sensor and information technology has advanced rapidly in recent years. This involves a variety of different sensor categories, i.e. different physical measures and different indicator principles. In combination with IT-based evaluation methods, this results in a wide range of possible applications for grassland farming. Compared to conventional methods of data collection, it is characteristic for the sensor and IT-based methods that data can be obtained with a high spatial and temporal resolution and that this is done more or less automatically. If these physical measurement data are translated into relevant state variables of the production system with the help of mathematical algorithms, then the state and the dynamics of the functioning of a production system can be described precisely. Table 2 exemplifies a compilation of fields of application of new sensor technology and data collection for grassland farming and which ecosystem services are addressed in each case. This compilation does not claim to be exhaustive. Rather, it is intended to show the basic application possibilities by means of examples. Accordingly, the references given represent only a small selection of the total literature available on this topic.

The sensors are mounted on various supports. For variables related to soil or plant stand, remote sensing techniques using satellite and airborne platforms are predominant. Proximal sensing methods using ground robots or ground vehicles are used less. The sensors record the spectral properties of the light reflected by the soil and plant stand. In particular, the information of visible light, the short-wave and near-infrared range is used via multi- and hyperspectral imaging. The information on the state of the production system that can be extracted from spectral data is particularly reliable when several sensors are combined (Wachendorf and Astor, 2019). Thus, if only one sensor is specified in Table 2, this does not exclude the possibility that better results can be achieved by adding further sensors. Animal-based sensors are used to record animal behaviour. These record the spatial position as well as the activity and resting behaviour of the animals. This can be used to estimate parameters of animal welfare and livestock performance. In research and development, these techniques are used successfully to determine state variables of plant growth and animal behaviour. However, their application is not yet widespread in grassland farming practice. A major challenge for the practical use of sensor data as a basis for management decisions, for example in pasture management, is the merging and processing of different data categories and of data at different spatial and temporal scales.

## Supporting grassland-based production systems with improved information

The technological innovations in data collection provide detailed information about the status of production factors and their changes. The diverse data on different variables must be linked and analysed together. In this way, multi-factorial functional relationships can be better identified and quantified. Rational decisions of the farming practice at the strategic (livestock production system) or operational level (grassland management) require such knowledge of complex functional relationships. If this is given, the performance of individual ecosystem services can be improved and trade-offs between different services reduced. This will be demonstrated using the example of multifunctional grazed grassland that provides various ecosystem services.

Table 2. Technological developments in information acquisition and processing and their potential use for improving grassland systems. For ecosystem service categories see Table 1 (own compilation).

| Domain/ Target | Ecosystem service | Technology/Sensors | Selected references |
|---|---|---|---|
| **Soil** | | | |
| Soil water | Food/Production: soil water availability, grass growth; Nature/Culture: maintaining diverse wet habitats; Climate: Conservation of soil carbon on organic soils; Water: replenishing ground and surface water resources | thermal imaging, evapotranspiration, energy fluxes, remote and proximal sensing | Brenner *et al*., 2018 |
| Soil fertility and soil organic carbon | Food/Production: nutrient and water provision to crop | hyperspectral imaging, applied to bare soil | Thaler *et al*., 2019 |
| **Grass sward** | | | |
| Botanical composition, valuable forage species, legumes | Food/Production: potential feeding value, timing grassland defoliation, adapting management strategy, assessing nitrogen fixation by legumes | visible light sensors, hyperspectral sensors, near infrared sensors | Wachendorf *et al*., 2018 |
| Identification of weeds, invasive species | Food/Production: weed control | visible light sensors, hyperspectral sensors, near infrared sensors, LiDAR | Brüninghoff *et al*., 2018 |
| Identification of rare species | Nature/Biodiversity: identifying single species, valuable grassland habitats, protecting species/habitats | visible light sensors, hyperspectral sensors, near infrared sensors | Cerrejon *et al*., 2021 |
| **Herbage** | | | |
| Herbage quantity | Food/Production: herbage growth rate, estimating potential current livestock performance | spectral sensors, LiDAR, structure from motion approach, ultrasonic sensor, rising plate meter | Murphy *et al*., 2021; Grüner *et al*., 2021 |
| Herbage quality | Food/Production: assessing potential livestock performance | multi- and hyperspectral sensors, near infrared sensors | Astor *et al*., 2020 |
| Fertiliser requirement | Food/Production: assessing nitrogen nutrition status of crop, fertilizer requirement<br>Water: efficient use of fertilizer nutrients, lowering emission risks into waters | multi- and hyperspectral sensors, near infrared sensors | Pellissier *et al*., 2015; Knoblauch *et al*., 2017; Gnyp *et al*., 2020 |
| Defoliation | Food/Production: optimizing timing and frequency of defoliation | near infrared sensors, satellite based radar sensors | Honkavaara *et al*., 2020; Malß *et al*., 2020 |
| **Livestock** | | | |
| Grazing behaviour/ animal welfare/ feed intake | Food/Production: utilization of feed resources, monitoring animal well-being, identification of sick animals, measuring herbage intake and animal performance, e.g. liveweight gain | Pedometer, GPS-logger, activity recorder, bite recorder | De Weerd *et al*., 2015; Riaboff *et al*., 2018 |
| **Added value** | | | |
| Quality of products and production process | Food/production: improved control of production process justifies marketing as premium product | automatic information system for monitoring and archiving production process | Mania *et al*., 2018 |
| **Society** | | | |
| Rewarding public goods | documentation/traceability/certification of production processes; will improve the provision of various ecosystem services | automatic information system for monitoring and archiving production process | Franke *et al*., 2012 |

The starting point is a concept of carbon gain and utilization in a grazing system with a perennial ryegrass sward developed by Parsons *et al*. (1983). Carbon conversion in a sward is controlled by the grazing pressure. The leaf area index determines photosynthetic performance and carbon allocation to the different plant parts. The age of the plant tissue, the extent of senescence and also the feed intake by the grazing animals also depend on the grazing pressure. If the production function of this grassland

is the dominating interest, then the grazing pressure would be adapted in a way that the highest feed intake per hectare is achieved. Knowledge of these functional relationships forms the basis for designing an efficient grazing system. Crop growth rate and daily nutritional requirements of the grazing livestock have to be balanced through targeted pasture allocation to the livestock in order to achieve a high feed conversion into animal product.

In addition to the production function, the processes shown in Figure 1 also influence other ecosystem services. If leniently grazed, a larger proportion of the carbon bound in the plant is returned to the soil 'past the animal's mouth' (Ebeling *et al*., 2020). This alters carbon sequestration. With low grazing pressure, the plants enter reproductive stages of development and produce fruits. In species-rich grassland, this is the prerequisite for maintaining plant species diversity (Isselstein, 2018). At the same time, it increases the attractiveness for grasshoppers and butterflies (Jerrentrup *et al*., 2014). Multifunctional pasture management must take into account the complexity of the system. This is a matter of a better insight not only into the single relationships but also into interactions with variable site conditions. Therefore, collecting a wide range of comprehensive information at the field and the farm level is required.

The analysis of this information makes it possible to reduce trade-offs between ecosystem services. Balancing the different services does not necessarily have to take place on a given area. It is also possible through spatial differentiation. Pasture management is a good example for this. Through small-scale fencing, which could be realized in the future through virtual fences with low labour input, the grazing pressure can be controlled in a differentiated manner, and thus different ecosystem services can be provided side by side. Such spatial differentiation is developed on extensively grazed pastures through preferential grazing behaviour even without fencing (Tonn *et al*., 2019). Controlling such spatial differentiations requires that the condition of the sward is recorded as continuously as possible and with high spatial resolution. Only then can the expected ecosystem services be reliably provided.

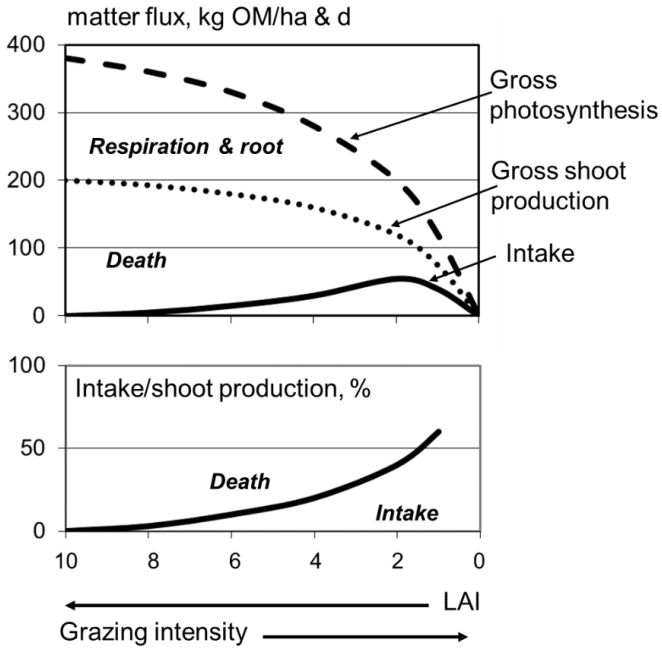


Figure 1. Effect of grazing intensity and corresponding leaf area index (LAI) on the rate of sward processes and intake efficiency (Parsons *et al*., 1983)

## Conclusions

Sensor technology, data collection and state variables description of the soil-crop-livestock system are already well developed. A broad application in practice is yet to come. This is not least due to the fact that the collected data do not readily represent useful information for management decisions. This requires the development of user-friendly tools that are capable of properly blending and analysing data from different categories so that well-based decisions for action can be made. Examples of such

decision support systems (DSS) already exist. PastureBase offers web-based support for the ruminant grassland farming industry while utilizing a broad data base combining national census data with farming enterprise data (Hanrahan *et al*., 2018). GrassQ (Murphy *et al*., 2019) and GrassCheck (Huson *et al*., 2020) are DSS that provide management tools to control grass cover and herbage quality for improved grazing management. There are more DSS being developed in different European countries with more targeted aims such as forage conservation. It is, however, important to mention that decision support tools should be integrated in a larger framework of improved information at the farm level. Usually, the farm structure and the kind of livestock production system are decisive for the performance and the management of the farm's grasslands. In the future, new ways should also be explored to make grassland farming better informed. In contrast to the usual top-down processes, bottom-up approaches are promising and have successfully been tested in some European research and development projects in recent years. The Inno4Grass (Krause *et al*., 2018), Eurodairy (Brocard *et al*., 2018) and HNV-Link (Herzon *et al*., 2020) projects investigated the extent to which experiences with technological innovations at the grassland farm level can be transferred to grassland farms in other regions or countries.

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# Towards an informed grassland farming – Sensors, platforms and algorithms

Bareth G.

*GIS & RS Group, Institute of Geography, University of Cologne, D-50923 Cologne, Germany*

## Abstract

Non-destructive monitoring of sward traits has been of management interest for more than a century. Key findings of early research works are still providing fundamental concepts for current proximal and remote sensing approaches to monitor forage mass and quality. For example, spectral absorption characteristics of plant pigments, vegetation cover, or sward height are considered in current analysis approaches. While established methods are based on vegetation indices, the latest analysis approaches, for instance those using machine learning, are considering multivariate analysis for nonlinear systems. The changing paradigm from high-cost to openly available satellite remote sensing data enables dense multi-temporal analysis. Another game changer is the use of Unmanned Aerial Vehicles (UAVs), which serve as carrying platforms for any sensing technology already being used in satellites or aircraft. Finally, combined analysis of spectral and structural canopy traits seems to provide robust estimators for forage mass and quality.

**Keywords:** remote sensing, proximal sensing, UAV, grassland, sward, forage, biomass, quality

## Introduction and background

Spatial decision support for grassland management requires spatio-temporal information on sward trait development (Schellberg *et al*., 2008). Destructive sampling is labour intensive, costly, and does not provide spatial coverage (Catchpole and Wheeler, 1992). Hence, field methods to non-destructively derive sward properties have been in development since the late 19$^{th}$ and early 20$^{th}$ centuries. Early approaches used visual plant growth patterns, cover densities, or clipping data to estimate forage productivity or grazing capacity (Faber, 1929). Pechanec and Pickford (1937) proposed weight estimates as being more precise than groundcover approaches. Another non-destructive approach was suggested by Evans and Jones (1958), who used plant-height x groundcover to estimate forage production. However, they found that it did not work on lodged vegetation. An improvement of the latter approach was the development of disc meters (Castle, 1976). Disc meters use a weighted metal plate that can be lowered on the sward, enabling readings of compressed sward height. They provide robust estimates of dry forage mass. This approach is still in use as Rising Plate Meters (RPMs) (Sanderson *et al*., 2001; Bareth and Schellberg, 2018). Latest developments to measure sward height and density are towable light curtains or ultrasonic sensors (Rennie *et al*., 2009; Fricke *et al*., 2011). However, all these presented methods lack complete spatial coverage.

In parallel, the first applications of airborne photography of vegetation (forests) were reported as early as the late 19$^{th}$ century (Albertz, 2009). Besides the progress in photography, developments in applied optics have enabled wavelength-specific reflection features of objects or a medium to be captured (Nutting, 1912), e.g., using spectroradiometers. These technologies have led to investigations of absorption spectra of plants caused, e.g., by chlorophylls (Weigert, 1916), carotenes, or xanthophylls (Miller, 1934). Airborne infrared and, later, multiband photography have been applied since the 1940s (Charter, 1959). An impressive paper on applying multiband reconnaissance by Colwell (1961) already showed crop disease detection for wheat and oats. Additionally, in that paper, a spectrum (400-900 nm) of grass is presented, which was captured by using a spectrophotometer. In the early 1970s, the milestone Landsat satellite mission was the start of continuous, multispectral remote sensing of the earth in medium resolution (Colwell, 1972; Markham and Helder, 2012). The potential of such satellite remote sensing for global crop forecasting from space was summarized in a research news reported in *Science* by Hammond (1975). Proximal, airborne and spaceborne remote-sensing data have therefore been available since the early 1960s (Haffner, 1966; Belward and Skoien, 2015). In 1969, the first volume of the *Journal of Remote Sensing of the Environment* was published, including work on agricultural applications (Gaussman et al. 1969) and on field spectrometer and multiband cameras (Lent and Thorley, 1969).

To summarize this rather extensive view into the history of non-destructive sward trait estimation and of remote sensing, most of the problems discussed nowadays were already being discussed a century ago, and some core principles of remote-sensing techniques were also developed more than 60 years ago. The scientific problem of non-destructively estimating forage growth, yield, and quality has not yet been solved and investigations are still underway as to how non-destructive measurements could support spatial decision making for managed grasslands (Rango *et al*., 2009; Reinermann *et al*., 2020). To reflect the current state of data acquisition and analysis approaches, I follow Marshall and Thenkabail (2015) and differentiate between methods to derive (i) spectral and (ii) non-spectral estimators of crop traits, and then (iii) summarize combined analysis approaches.

## Analysis of spectral crop traits

According to Marshall and Thenkabail (2015), spectral techniques rely only on the distinct and unique spectral absorption and reflection properties of crop canopies. This is a key finding because, e.g., nitrogen does not have a distinct and unique spectral absorption and reflection characteristic (Berger *et al*. 2020) whereas chlorophylls do (Thenkabail *et al.,* 2019). Detailed descriptions of characteristic absorption wavelengths for vegetation are given by Kumar *et al*. (2003). Figure 1 shows a spectrum of a grass canopy derived with a field-portable spectroradiometer and characteristic absorption features are marked and described. Additionally, multispectral bands of the multispectral satellite mission Sentinel-2 are visualized. Four broad bands are available in 10 m spatial resolution: blue (B), green (G), red (R,) and near-infrared (NIR). Six bands are available in 20 m spatial resolution: two in the red-edge region, two in the NIR, and two in the shortwave-infrared (SWIR). In Figure 1 it is of interest that there are absorption bands in the NIR/SWIR domain of cellulose, lignin, and protein, which are directly linked to forage quality in terms of crude protein, neutral detergent fibre (NDF), and acid detergent fibre (ADF) (Biewer *et al*., 2009).

Many multispectral satellite sensors share wavelengths similar to those presented in Figure 1 (e.g., Landsat). The bands are usually used to compute vegetation indices (VIs) that utilize two or more bands, such as the Normalized Difference Vegetation Index (NDVI), which was first published in 1973 by Rouse *et al*. as the band ratio parameter (BRP), but is based on work on normalized differences by Kriegler *et al*. in 1969 (Crippen, 1990). The NDVI is NIR minus R divided by NIR plus R. An almost endless number of studies now exist on how to use the NDVI for vegetation monitoring (biomass, N, stresses etc.) and many more VIs have been developed. VIs are still widely applied and under investigation. Roberts *et al.* (2019) provide a comprehensive review on available VIs for vegetation structure, canopy biochemistry such as pigments, moisture, and plant physiology.

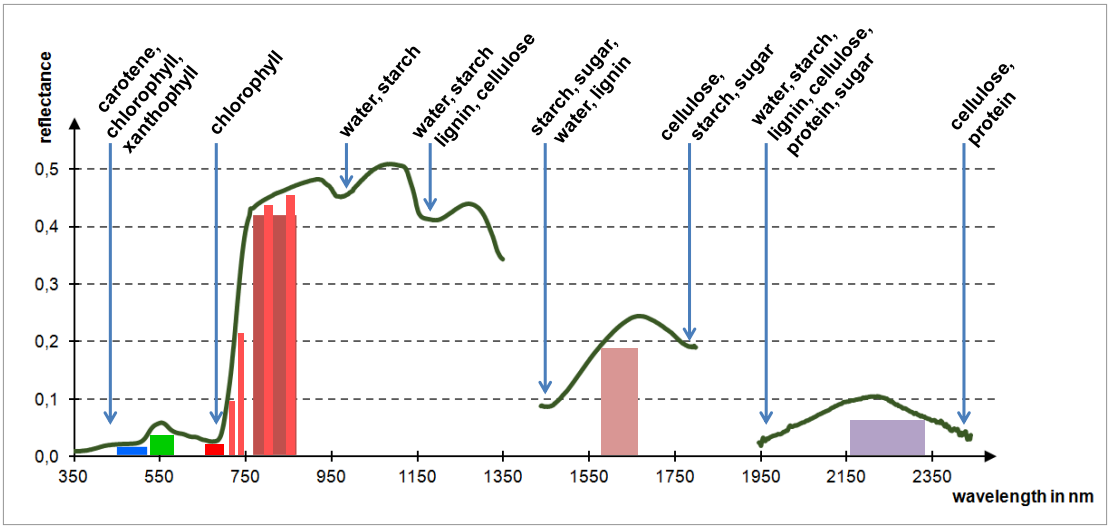


Figure 1. Canopy reflectance acquired by Ulrike Lussem with an ASDI field-portable spectroradiometer (FieldSpec-3) in full range (350-2500 nm). Characteristic absorption features are described as in Kumar *et al*. (2003) and Roberts *et al*. (2019). The coloured columns approx. represent spectral bands of Sentinel-2 in 10 m and 20 m spatial resolution (https://sentinel.esa.int/web/sentinel/technical-guides/sentinel-2-msi/msi-instrument).

Figure 1 clearly shows that characteristic absorption features to derive, e.g., forage quality, are not or only partly covered by satellite sensors. One parameter to evaluate forage quality is crude protein content, which is determined by destructive biomass samplings and laboratory analysis of total N content. But chlorophyll, which has distinct absorption features, is not fully representative of N content. Therefore, Berger *et al*. (2020) and Aasen and Bareth (2019) propose further investigations of the potential of absorption features in the NIR/SWIR domain for estimating, e.g., N content, and Tilly and Bareth (2019) suggest using N relations with, e.g., biomass.

Another problem is spatial resolution. In my opinion spatial decision support for forage management requires a spatial resolution of below 10 m to capture spatial heterogeneity in growth and flora of grasslands. Only few sensors can provide such a spatial resolution. Sentinel-2 provides 10 m resolution as open data but, as shown in Fig.1, only captures four rather broad spectral bands. Other datasets are provided, e.g., by Planet (www.planet.com) in 4 m and 1 m, or by Maxar (www.maxar.com) in 2 m and 0.5 m. The latter even provide eight SWIR bands in 4 m. Both are commercial products and can be costly, and thus only Sentinel-2 is available on an affordable scale for a continuous, multitemporal monitoring of grasslands for management purposes (Klingler *et al.,* 2020; Schwieder *et al*., 2020).

Almost every optical remote sensing technology available for satellites is now available for airborne remote sensing or can be mounted on Unmanned Aerial Vehicles (UAVs). In addition to multispectral sensors, numerous hyperspectral pushbroom and frame sensors are available for airborne or UAV-based data acquisition (Aasen *et al*., 2018, Bareth *et al.,* 2011, Colomina and Molina 2014). The advantage of hyperspectral sensors is that they provide almost continuous very narrow bands (< 10 nm). For example, the first hyperspectral satellite sensor in medium spatial resolution (Hyperion; 30 m) provided 220 bands from 400 to 2500 nm (Pearlman *et al*., 2003) and the next hyperspectral satellite mission EnMap is scheduled for 2021 (Guanter *et al*., 2015). Spatial resolutions of airborne or UAV-based hyperspectral sensors are much higher and range from centimetres to metres (Capolupo *et al*., 2015). Wijesingha *et al*. 2020 reported good prediction results for forage quality by using a UAV-mounted imaging spectrometer with 126 narrow bands. However, these sensors usually cover only the wavelength range between 350 and 1000 nm, and there have been few studies with full range sensors (350-2500 nm) (Camino *et al*. 2018; Honkavaara *et al.,* 2016; Siegmann *et al.* 2019). Certainly, a research niche in capturing distinct absorption features of grass canopies is to be found in multispectral narrow band sensors that also cover the VIS/NIR/SWIR domain, such as in the study by Jenal *et al.* (2020).

In terms of data analysis, hyperspectral data also can be used to derive narrow band VIs that follow the equations of the above-mentioned VIs. Due to the enhanced spectral resolution, the focus in data analysis is on utilizing the complete spectral information. In line with the concept of VIs, in lambda-lambda plots all possible wavelength combinations can be analysed and visualized to determine best narrow band combinations (Thenkabail *et al*. 2019). Principle Component Analysis (PCA) is applied to eliminate redundant wavelengths. Other applied methods are, e.g., Partial Least Square Regression (PLSR) or Support Vector Regression (SVR). Machine-learning approaches that identify patterns in data sets are becoming more popular (Lary *et al*. 2016), and lately deep-learning approaches using artificial neuronal network (ANNs) for big data sets have shown promising potential in analysing spectral data for grasslands (Ma *et al.* 2019, Näsi *et al*. 2018). However, it is yet not clear which spectral analysis method is superior compared to established VIs or lambda-lambda plots. Fig.2, which shows a lambda-lambda plot for chlorophyll of rice leaves, illustrates that some wavelength regions provide a high estimation using a two-band VI equation.

## Analysis of non-spectral crop traits

Marshall and Thenkabail (2015) list as *in situ* non-spectral canopy traits, e.g., vitality by visual assessment, crop height, fraction of vegetation cover (FVC), and compressed canopy height by RPM measurements. As mentioned in the introduction, these are some of the measures discussed and investigated by grassland scientists a century ago. But most interesting is the approach by Evans and Jones (1958), who proposed using plant height times ground cover (PHxGC) to estimate forage production non-destructively. The measurement of crop height and crop growth has been done in field experiments with rulers, or later with RPMs. In the late 1980s, new technologies emerged that enabled crop height to be measured more efficiently. Hutchings *et al.* (1990) successfully developed and tested

an ultrasonic rangefinder stick to measure sward heights. Fricke *et al*. (2011) also used an ultrasonic sensor to identify high $R^2$ between forage mass and measured sward height. Latest improvements use ultrasonic arrays to measure vertically through the pasture (Legg and Bradley, 2020). However, and again, these ultrasonic measuring techniques do not enable spatially continuous data acquisition.

In the first decade of the 21st century, capable surveying devices, namely terrestrial laser scanners (TLS), became popular. TLS produce accurate and dense 3D point clouds. Based on this technique, Hoffmeister *et al.* (2010) developed the idea of multitemporal Crop Surface Models (CSM) for spatial crop height monitoring. A CSM is a very high resolution (< 5 cm) Digital Surface Model (DSM). Fig.2 shows the CSM approach. By acquiring a Digital Terrain Model (DTM) after sowing, which serves as the base height, GIS software can be used to subtract the DTM from later CSMs, resulting in absolute metric plant height data. Tilly *et al.* (2015) and Hoffmeister *et al.* (2016) successfully tested the approach. Investigations by Cooper *et al.* (2017) and Schulze-Brünighoff *et al.* (2019) showed that TLS-derived sward height also works well for biomass estimation in grasslands.

Fifteen years ago, software developments from computer vision and photogrammetry led to user-friendly Structure of Motion (SfM) and Multiview Stereopsis (MVS) analysis tools, which could be used to analyse overlapping image data obtained by UAVs (Harwin and Lucieer, 2012; Granshaw, 2018) to produce dense 3D point clouds. Bendig *et al*. (2013) successfully transferred the CSM approach to a UAV-derived image data analysis workflow to derive crop height for biomass estimation. Nowadays, UAV-based data acquisition and SfM/MVS analysis is an established method for determining crop or sward height (Bareth and Schellberg, 2018; Grüner *et al.,* 2020; Lussem *et al.,* 2020; Viljanen *et al.,* 2018). Over the last ten years, UAV-mounted laserscanning (UAV-LiDAR) has become more popular as an active remote sensing method to directly capture 3D point clouds for vegetation monitoring (Jaakkola *et al.,* 2010; Wallace *et al.,* 2012). Successful investigations to derive plant height as an estimator for biomass using UAV-LiDAR have been undertaken for crops by Li *et al.* (2015) and by ten Harkerl *et al.* (2020), and for grassland by Wang *et al*. (2017).

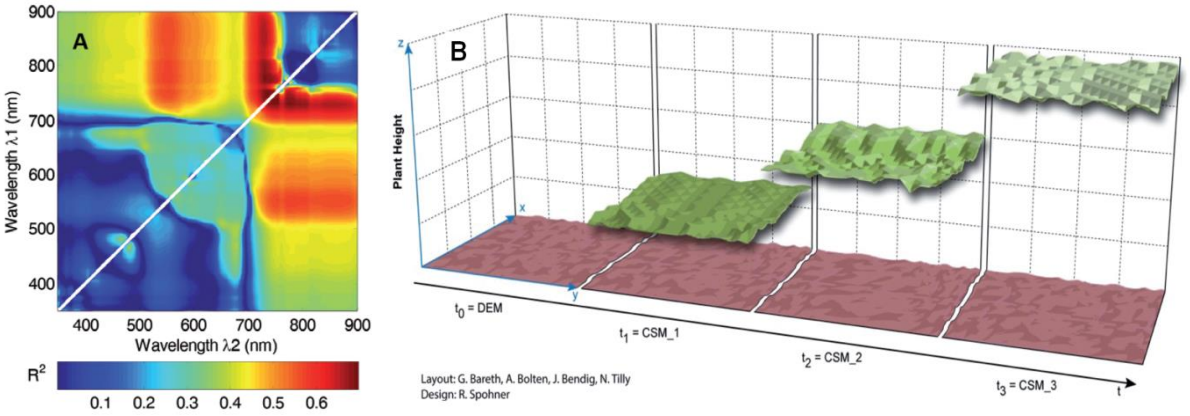


Figure 2. (A) A lambda-lambda plot of the NDVI equation for all possible wavelength combinations against chlorophyll content (Yu *et al*. 2015); (B) the Crop Surface Model approach. The DEM represents the Digital Terrain Model (DTM) (Bendig *et al*. 2013)

While laser scanning is only available on UAV or airborne platforms and not from satellites, radar remote sensing (SAR) is another active remote sensing method that is also available from satellites in spatial resolutions below 10 m (Sentinel-1, Radarsat-2, TerraSAR-X, TanDEM-X, Cosmo SkyMed, PAZ SAR). The advantage of SAR is its almost weather-independent ability to acquire data, allowing clouds, fog, smoke, and haze to be penetrated. Currently X-band (λ: approx. 3 cm) and C-band (λ: approx. 5.5 cm) are available from space in the desired spatial resolution of below 10 m. However, again, only Sentinel-1 are open data while the other SAR data are costly. SAR data have been successfully exploited for grassland monitoring (Ali *et al*. 2017; Crabbe *et al*. 2021).

## Combined analysis of spectral and non-spectral crop traits

The idea of combining data sets from multiple sensors has become more popular since the 1990s (Ehlers 1991). Work on monitoring winter wheat biomass by a combination of hyperspectral (Hyperion)

and radar (Envisat) satellite remote sensing using multivariate regression analysis was published by Koppe *et al*. (2012). The same approach was applied by Bendig *et al*. (2015), combining hyperspectral field data analysis with UAV-derived crop height for winter barley. Both studies could prove that such a combined analysis of spectral and non-spectral data yields robust estimations of biomass, which was also described by Banerjee *et al*. (2020) for wheat in a phenotyping experiment in Australia. Similar data analysis in grasslands was conducted by Fricke and Wachendorf (2013) and Pittmann *et al.* (2015). Bareth *et al.* (2015) proposed a simple combined VI, the Grassland Index (GrassI), which sums the UAV-derived sward height with a VI derived from the same RGB image data, the RGBVI. GrassI was evaluated by Viljanen *et al.* (2018) as a strong predictor of forage mass. However, in the same study, the Excess Green Index (ExG) combined with sward height and multiple linear regression (MLR) and a random forest estimator (RF) performed slightly better. The key findings again prove that combining sward height with VIs results in robust estimators for forage mass. Latest studies on the advantages of combining structural and spectral sward canopy properties using machine learning are given by Grüner *et al.* (2020) and by Oliveira *et al.* (2020) for forage mass and quality.

## Discussion, conclusions and outlook

In principle, requirements are similar for spatial management support in forestry, crop production or grasslands. Numerous studies on precision agriculture (PreAg) have been available since the late 1980s (Mulla, 2013). Precision agriculture for managed grasslands is discussed by Schellberg *et al.* (2008). Proximal and remote-sensing techniques play an essential role in these approaches. Quantifying spectral canopy properties from characteristic absorption domains in the reflectance spectra is widely applied but generally requires good weather and can be retrieved from satellites only under clear sky conditions, which is impractical for farming purposes. UAV and airborne spectral data acquisition also favours clear sky conditions, or at least stable solar irradiance, e.g., continuous cloud cover. However, proximal sensors such as tractor-mounted spectrometers, especially active ones, can also be operated under varying irradiations (Kipp *et al*., 2014). More robust seem to be remote-sensing methods that retrieve non-spectral or structural canopy traits such as sward height or sward density. Evans and Jones (1958) proposed structural canopy traits for non-destructive estimation of forage production and suggested using plant height times groundcover. In this context, methods from photogrammetry and surveying, such as stereophotogrammetric analysis or laserscanning, are important in deriving 3D point clouds. Both methods and ultrasonic approaches can be used for proximal sensing in the field or mounted on machinery such as tractors.

However, UAV platforms are also capable of deriving these non-spectral canopy traits timely, cost-effectively, and in appropriate spatio-temporal resolutions. From satellites, high-resolution radar remote sensing has not yet been fully exploited for agricultural applications or for grassland monitoring. As an almost weather-independent data acquisition method, radar remote sensing can provide timely canopy traits in appropriate spatio-temporal resolutions (Koppe *et al*., 2013; Crabbe *et al*., 2021). Finally, the largest potential to provide robust estimators for sward traits are combined analysis methods of spectral and non-spectral canopy traits, which perform better on multi-temporal scales (Bendig *et al.,* 2014, Reddersen *et al*., 2014; Moeckel *et al.* 2017; Grüner *et al.* 2020; Olivejra *et al*. 2020). In this context, machine-learning methods have become more important.

For future use in spatial decision support for agronomic or grassland management, fully automated openly available radar remote sensing and combined analysis with optical satellite data in a scale below 10 m can provide desired spatio-temporal resolution and are more cost-efficient. However, UAV-based remote sensing seems to have an even larger potential, also from an economic perspective. The vision is that farmers will start the farm's UAV fleet just by pressing a button or on a regularly automated, e.g., daily, scale with ensuing data acquisition, data transfer into cloud storage and analysis. Within a short, almost real time or in few hours, they will then have automatic access to visualization of the current status of canopy properties including management suggestions. Latest 5G technology is not yet being considered but is the final missing link in the envisaged data management architecture of Bareth and Doluschitz (2010). That architecture, which builds on various existing technologies, could provide highly automated spatial decision support for PreAg and precision crop management. That this UAV future is close can be seen by the progress of Amazon Prime's air delivery using UAVs, and the first UAV deliveries made by UPS for medical services in 2020 (CNN 2020).

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# Theme 1. Biomass and quality characteristics

# Drone-based remote sensing of sward structure and biomass for precision grazing: state of the art and future challenges

Bindelle J.[1], Da Silva Neto G.F.[2], Kokah Essomandan U.[1], Carvalho P.C.F.[2] and Michez A.[3]

*[1]Liège University, Gembloux Agro-Bio Tech, Passage des Déportés, 2, BE-5030, Gembloux; [2]Universidade Federal do Rio Grande do Sul, Faculdade de Agronomia, Avenida Bento Gonçalves 7712 - Bairro Agronomia - BR-91540-000 - Porto Alegre, RS; [3]University Rennes 2 LETG (CNRS UMR 6554), Place du Recteur Le Moal, F-35043 Rennes*

## Abstract

From an understanding of the ecological basis of grazing from both the perspectives of plants and herbivores, we examine why sward structure and biomass are key grassland vegetation traits for monitoring of grazing management. We review how unmanned aerial systems (UAS) have been used to measure these traits through spectral analysis and 3D modelling, and discuss how UAS remote sensing could empower disruptive innovations for grazing management based on the ecological processes of plant-animal interactions and the spatial heterogeneity inherent to pastoral ecosystems.

**Keywords:** unmanned aerial systems, sward height, biomass, pasture, precision grazing

## Introduction

The past fifty years have seen a surge in the development of remote sensing solutions to monitor the earth's ecosystems (Sparrow *et al*., 2020). Grasslands cover a significant share of the world's ice-free land mass and are at the heart of the most criticized as well as the most sensitive livestock farming systems (Sollenberger *et al*., 2019). From the early years of remote sensing technologies becoming available, pasture scientists have been interested in their potential for monitoring and management of grazing ruminants because traditional field methods are time-consuming, and remote sensing offers an alternative that permits rapid evaluation of large geographical areas (Tappan and Kinsler, 1982). In the past decade, there have been important developments in the use of unmanned aerial systems (UAS), commonly called drones, for the monitoring of grassland biomass and sward structure in research, overshadowing more established airborne imagery methods due to their relatively low cost and greater flexibility (e.g. Rango *et al*., 2006; Wang *et al*., 2016; Viljanen *et al*., 2018; Michez *et al*., 2019, 2020; Jenal *et al*., 2020). These developments enable the use of UAS as possible key tools of decision-support systems for grazing management based on remote sensing of grasslands besides or in combination with satellite-based imagery. Nevertheless, to achieve such an objective, a strong knowledge integration must be established between pasture, remote sensing, and modelling scientists. In this review, starting from a definition of grazing, we explain why sward structure and pasture biomass are relevant traits of grazed vegetation to be monitored from a grazing management perspective and how these traits are traditionally measured by graziers. Then, we review what UAS can offer to sense those traits and how their use can provide a methodological change in the monitoring of grazed grasslands.

## Sward structure and biomass are key traits for grazing management

Grazing is defined as the action of an herbivore to feed on growing herbage. Behind an apparent simple definition hides complex direct and indirect interactions, as well as feedback mechanisms, between the plant and the animal compartments of the pastoral ecosystem. From an ecological perspective, grazing can be seen as a predator-prey relationship (Venter *et al*., 2019), in which the prey, i.e. the plant, should not be killed by the herbivore that feeds on it. The preservation of the ability of the plant to regrow after being defoliated by the herbivore is a pivotal target of any grazing management method (Hodgson, 1990). Grazing takes place at the interface between the plant and the animal. What happens before the grazing event is related to plant-based processes (growth and senescence), and what happens with the consumed forage relates to the herbivore, its digestion, and metabolism. The art of grazing management lies in making sure that both the plant and animal requirements are met when grazing takes place. From the perspective of the plant, grazing can be seen as a sudden reduction in above ground foliage and, thus, its capacity to capture incident photosynthetically active radiation (PARi) from the sun and convert it into plant above- and below-ground biomass. Usual targets recommend grazing in grass swards to be

initiated when plant foliage reaches 95% of light interception (LI) (Korte *et al*., 1982). This point corresponds to the end of the linear phase of the sigmoidal forage growth curve described by Brougham (1955) and, compared to points where the LI exceeds 95%, it should result in greater forage production with a higher proportion of leaves and a lower proportion of dead material (Silva *et al*., 2015). Among the different traits that characterize sward structure such as its height, leaf/stem ratio, ground cover and bulk density, the leaf-area index (LAI) is critical owing its positive relationship with the ability of the plant to intercept light (Gastal and Lemaire, 2015). Measuring LAI in the field is not an easy task and, research purposes set aside, LAI is not used in practice as an indicator for grazing management. More indirect relationships can be drawn between LAI and proxies easier to measure in the field such as the standing biomass or sward height (King *et al*. 1986). While clipping vegetation plots is the reference method to measure standing biomass, various non-destructive alternatives have been proposed for practical use. The most successful is the rising plate meter (RPM) which is also available in versions that allow a spatialization of a high number of measurements when connected to a GPS (French *et al*., 2015). Sward sticks are the reference tool for sward height. Their use is also non-destructive, and they can also be used to provide spatialized data. However, sward measurement by RPM and sward sticks are both time-consuming procedures and require an operator to sample the whole area of interest in the field.

Capturing PARi for growth is not the only factor influencing the efficiency of the conversion of solar energy into edible plant tissues. The whole balance between the production of new leaves, the senescence of older leaves, and the storage and mobilization of energy reserves in the growth preceding and following a defoliation event must be considered. Focussing on the efficiency of these plant growth and regrowth cycles, the specific 3-leaf stage was proposed as a target to initiate grazing in perennial ryegrass (*Lolium perenne*) pastures (Fulkerson and Donaghy, 2001). Although leaf stage during regrowth was considered to be a useful indicator of grazing readiness by Chapman *et al*. (2012), the latter also stated that it should not be used too rigidly. More importantly, such a 3-leaf stage does not correlate constantly across the whole grazing cycle with the other sward-based proxies of standing biomass and height.

Assessing grazing conditions of a pasture is not only about how much biomass or what structure the to-be-grazed sward should have. It is also about how much should be left after a grazing event of a patch in continuous grazing, or on a paddock in rotational grazing, in terms of residual LAI, height, and biomass. This will determine for how long, in terms of growing degree days (GDD), the plant should be allowed to recover before experiencing a new defoliation. Here too, several targets are proposed depending on the objective, the most common ones being the maximization of harvest or grazing efficiency (Scarnecchia, 1988).

From the animal's perspective, grazing is a very complex process. Animals do not see the vegetation of a paddock as a whole but rather as a multitude of potential bites. Grazing is a multiscale process, heterogeneous in space and time, involving a combination of one-time confined choices to perform individual bites on specific feeding stations to large movements of the animals across the whole pasture over meals, days, and months. Indeed, the major limitation for grazing ruminants to fulfil their daily feed requirements is usually set by the limited amount of time they have to collect their daily forage allowance through tens of thousands of individual bites (Carvalho *et al*., 2013). Recent work has shown that a sward structure does exist, mainly determined through its height, that allows herbivores to maximize their short-term intake rate (STIR) through an optimal combination of bite mass and time required to manipulate the vegetation before severing and swallowing it. Plotting changes in STIR against sward height usually produces a bell-shaped curve that is specific for each forage species. Hence, setting grazing management targets based on this animal-oriented concept also requires the monitoring of the sward. For example, in *Lolium multiflorum* and *Cynodon dactylon* the sward height which allows animals to maximize the STIR is 19 cm. For *Avena strigosa*, it is 29 cm (Carvalho, 2013). Also, heterogeneity can enhance the functional response of herbivores (Pontes-Prates *et al*., 2020) and minimize grazing time. Thus, monitoring the vegetation at a high frequency with UAS remote sensing in real time has the potential not only to identify and keep target sward heights but also its degree of heterogeneity (sward height variation), incorporating the concept of heterogeneity in the management of grazing systems.

## Why spatializing the monitoring of sward structure and biomass?

Beyond the well-known spatial heterogeneity in soil and vegetation attributes, grazed grasslands are necessarily heterogeneous because of how animals perform their bites. Firstly, they remove a diversity of plant material by selecting plant species and specific parts of plants (nature of plant organs) that are variable in chemical composition and mass, which makes up the heterogeneity of bites. After one single bite that needs a just second or more to be taken, the regrowth takes several days to weeks depending on the residual photosynthetic capacity, the energy reserves of the plant and the environmental factors (i.e. temperature, radiation, water supply, etc.). Hence, herbivores can graze only a small proportion of the whole grazable area each day (Schwinning and Parsons, 1999). Secondly, when performing bites over one or several feeding stations, animals look for specific plant species, plant parts of a given species, and within a given species for plant structure that allows them to optimize intake rate as discussed above. Moreover, the selection process is not entirely deterministic. There remains some uncertainty as to exactly where the animals choose to take bites. Third and finally, the efficiency in the grazing process usually decreases with grazing-down level, as the lower animals get in the vegetation, the lower the harvest per bite while still on average 50% of the residual sward height is taken per bite. As a consequence, animals turn the grazed pasture into a vegetation with patches with different regrowth stages whatever the grazing method (Pontes-Prates *et al*., 2020). From this understanding of the ecology of grazing, relevant key indicators of grazing condition are once again the sward biomass, since it allows the calculation of forage allowance and hence determines the stocking rate of pastures, and the sward height for its impact on both animal selective grazing behaviour and plant growth dynamics.

## UAS remote sensing of grazing conditions

Remote sensing can be used for the characterization of vegetation in various contexts, from grazed natural rangelands to ungrazed pure-stand phenotyping plots. The characterization of grasslands has been tackled in various ways in the literature. Differing approaches result from four main factors: (1) the targeted vegetation traits, (2) the sensor used, (3) the platform onboarding the sensor(s), and (4) the area to characterize as well as the grain (scale factor). In terms of platforms, remote sensing of grazed vegetation can be investigated from the ground perspective of human operators (Safari *et al*., 2016; Rueda-Ayala *et al*., 2019) to airborne (Möckel *et al*., 2016) and spaceborne approaches (Reinermann *et al*., 2020).

Starting with the grain (i.e., the ground size of the highlighted traits) and the extent (the area covered), both are constrained by the sensors and the platform. On one side of the gradient, ground-based remote sensing typically offers sub centimetric spatial resolution (e.g., Andriamandroso *et al*., 2017b), but fails to cover significant areas hampering operational applications for practitioners. On the other side, satellite remote sensing can have a global coverage of the earth's surface at a very low cost for the end-user but with spatial resolution above 10 to 30 metres for free-of-charge constellations (e.g., Sentinel and Landsat programs). Between these two extremes, airborne remote sensing, and more specifically UAS can cover areas relevant from a grazing management perspective (>10 ha per survey) while providing imagery at a very high spatial resolution (< 0.1 m) to face the challenge of precision grazing. Compared to manned airborne remote sensing, UAS are more versatile tools that can be deployed on demand by the end-user to synchronize the acquisition of aerial imagery with the need for data on the field. As they fly at very low altitudes (generally < 100 m above ground level), they can collect data under more diverse weather conditions than other remote-sensing solutions, especially on cloudy days.

## Which sensor for which UAS application?

UAS applications are mainly driven by the sensor which is mounted. Most publications focus on the vegetation with passive spectral remote sensing using off-the-shelf visible (Red Green Blue, RGB), near-infrared (NIR) multi- and hyperspectral cameras. These three types of sensors display strong differences in terms of resolution, costs, and ease of use. RGB cameras offer, at very low-cost and with a high spatial resolution (> 15 MPx), lower quality spectral information as they only cover the visible range of the electromagnetic spectrum and present important overlapping between the spectral bands. Hyperspectral cameras can sense a large portion of the electromagnetic spectrum (from 400 to 1500 nm) with a high spectral resolution (bandwidth < 10 nm) but a lower spatial resolution. Multispectral

cameras can be seen as an in-between solution, covering the visible and NIR spectrum at higher spatial resolution (around 12 MPx for the best) but with lower spectral resolution (5-6 spectral bands). Multispectral and hyperspectral imageries allow computing true surface reflectance (i.e., the proportion of light reflected by the ground surface) after a radiometric calibration process, although the quality of UAS reflectance is still questioned by several authors (Manfreda *et al*., 2018). Indeed, state-of-art procedures include the use of a downwelling irradiance sensor as well as calibrated reflectance panel. Nevertheless, the placing of the sensor and the UAV above the panel can shade a significant proportion of the hemisphere, leading to bias which can account for up to 15% under cloudy conditions (Aasen and Bolten, 2018).

Imaging sensors like multispectral and RGB cameras also allow the derivation of 3D information using structure from motion (SFM) photogrammetry (Westoby *et al*., 2012). The typical 3D output is a digital surface model (DSM) describing the absolute altitude of the sward top canopy layer. Combined with a digital terrain model (DTM), digital sward height models can be derived at unprecedented spatial resolution and over extents beyond comparison with traditional field approaches. LiDAR (Light detection and ranging) scanning devices represent the silver bullet technology in terms of 3D remote sensing. This active remote sensing technique emits high frequency laser pulses and records the reflected pulses to precisely locate the scanned surface. This results in a 3D point cloud which can be used to produce high resolution sward height maps. Most LiDAR systems can record several returns from a single laser pulse when it reaches an object with multiple layers. Unlike SFM point clouds, LiDAR surveys can yield information across the whole vertical sward structure: top canopy leaves, intermediate leaves as well as the ground (Wijesingha *et al*., 2019). The major limitation for UAS LiDAR remains its cost (> 50 k$ in 2021) as well as the weight of the sensor (> 1 kg) which hinders its use in low-cost micro drones (< 2 kg). The quality of 3D model-based sward height estimates is commonly evaluated through the accuracy of simple linear regression with a reference sward height. Authors globally agree on the high potential of UAS remote sensing to describe the sward height, with $r^2$ of ca. 70% (up to 91% for Bareth and Schellberg, 2018) depending on the methodological approach. Objective and quantitative comparisons between studies are hindered by the variety of reference sward height measurement approaches as well as the spatial scale upon which the model is fitted. For example, the field height measurement can be discretized from nearly the exact point of measurement (4 $cm^2$, Michez *et al*., 2020, $r^2$ = 48%), to higher areas such as a dropping 10-cm diameter (50 g) disk (Formosso *et al*., 2018, $r^2$ = 70%) or the traditional rising plate meter measuring compressed sward height (Bareth and Schellberg, 2018, $r^2$ = 86%), which is actually more an indirect estimate of biomass than a sward height measurement.

UAS data can be used to model other key structural traits, like sward biomass or LAI, generally through the use of empirical modelling. Sward height can be used as a predictor of biomass even if biomass estimates are greatly improved by the integration of spectral (Michez *et al*., 2019) or even textural information (Grüner *et al*., 2020). UAS biomass empirical models present a performance based on $r^2$ typically ranging around 70% using RGB camera to the almost perfect fit for the best reported case by Vijnalen *et al*. (2018) who reached a $r^2$ of 96% for DM yields by combining very high-resolution 3D models from a RGB camera to hyperspectral imagery with an innovative modelling strategy (random forest machine learning). Similar modelling approaches were applied to LAI with high modelling accuracies, as highlighted by Fan *et al*. (2017) ($r^2$ = 0.88) and Lu *et al*. (2018) ($r^2$ = 0.81). Such modelling approaches usually integrate spectral information through vegetation indices (VI) which are arithmetic combinations of different spectral bands. The differential reflection across surface heterogeneities allows enhancing the contrast in the observed vegetation. VI also allow the reduction of signal artefacts notably related to in-flight varying light exposures. VI typically integrate a combination of the NIR (700 nm to 1300 nm) and the visible spectral ranges (400 nm to 700 nm) to highlight differences among photosynthetically active vegetation whose leaves absorb relatively more red than infrared light. Depending on the spectral resolution and the number of spectral bands captured by the sensor, the diversity of VI which can be investigated is very broad. The Normalized Difference Vegetation Index (NDVI) is the most renowned VI and was firstly introduced by Rouse *et al*. (1973). It is a typical multispectral VI of plant vigour which can be processed from UAS multispectral sensors but also by modified RGB sensors by removal of the infrared low-pass filter. Strictly visible VI are also well investigated by UAS scientists, even if their performance is lower than those computed with multispectral or hyperspectral cameras since the original spectral information is lower in quality (spectral resolution and overlapping bandwidth).

## Disruptive potential of UAS-based measurements for grazing management

Most UAS studies investigated the use of UAS on a single date and on ungrazed experimental sites, and they have not discussed much further than the fitted model accuracies, notably overlooking the proper integration of UAS remote sensing as an operational tool for field practitioners. While the use of straightforward linear regression allows to reach satisfying modelling accuracies, the model parameters are clearly site and weather dependent when integrating UAS spectral information. Indeed, the calibration and standardisation of UAS spectral data is still known to be problematic for multi-temporal quantitative approaches (Manfreda *et al*., 2018). The site-dependency of the linear regression parameters integrates complex properties of study sites like sward structure and species composition in relation to management practices or meteorological conditions. Such issues could be addressed by the integration of more mechanistic modelling approaches allowing a better understanding of the aforementioned site-specific parameters. More complex nonparametric modelling approaches based on deep learning strategies are also still missing in the context of precision grazing science. Innovative data curation strategies can also combine the best of both worlds (i.e. airborne and field sensing). For example, in the specific case of sward structure, limited field measurements can be used to adapt linear model parameters to local conditions as suggested by Forsmoo *et al*. (2018): 10 field measurements were sufficient to re-calibrate a linear UAS sward height model for a mixed *Lolium perenne-Trifolium pratense* sward.

As the spatial resolution of RGB sensors keeps rising, direct measurement of key traits meaningful from the grazing ecology perspective can be considered. For example, the precise delineation of sward leaves could be performed directly from the UAS images through millimetric imagery and effective deep learning image analysis. Such fine scale delineation could open up new opportunities like the precise identification of key phenological stages (e.g., the 3-leaf stage in ryegrass) or move from LAI UAS estimates from empirical modelling to direct foliar surface measurements. The use of multi-temporal UAS remote sensing offers unique opportunities for monitoring plant-animal interaction at very high spatio-temporal resolution. This is essential to the implementation of sound precision grazing management where the monitoring of ingestive behaviour of individual animals (Andriamandroso *et al*., 2017a), and the vegetation structure in time and space with a high degree of refinement, are used to better manage the processes and the complexity of pastoral ecosystems. More importantly, precision grazing must enable innovative grazing practices in which vegetation structures are offered to grazing animals not only to enhance their production but also other ecosystem services (e.g., Enri *et al*., 2017). For this purpose, heterogeneity is seen as an inherent characteristic of these environments and stocking methods are not trying to iron them out but rather explore them to yield positive effects on the ecosystem. While the spatial distribution of biomass within small size paddocks seems less critical, as discussed above, the distribution of sward height and structure is relevant down to the level of the elementary component of the grazing process, the bite, an area as small as 7.5 to 13.0 cm² for sheep and goats (Gordon *et al*., 1996) and 45 to 90 cm² for cattle (Benvenutti *et al*., 2006). In this context, UAS remote sensing could provoke a quantum leap in bringing refined information that none of the previous field based or remote sensing methods is able to provide, such as the horizontal distribution of plant species, the vertical distribution of the pasture structure, or the nutritional status of the plants (Astor, 2021). For example, in vegetation structures where pseudostems (vegetative) or stems (reproductive) represent a barrier to bite depth, bite mass is related more to lamina or regrowth length than simply the sward height (Gordon and Benvenutti, 2006). Hence, multilayer 3D models of the sward internal structure from UAS LiDAR flights could provide meaningful information for grazing management, and by allowing to measure bite depth and vertical distribution of LAI better, it would enable a better prediction of post-grazing regrowth potential. Such models could also determine the vertical distribution of plant species in multispecies pastures, in addition to the more obvious horizontal distribution of patches.

## Conclusions

Field-based measurements of pasture biomass and sward height are both time-consuming and hard to perform at a high level of spatial resolution. Hence, UAS-based remote sensing could become the reference measurement for these parameters because it presents advantages such as the speed of measurements, inherent spatialization of data, and greater precision, making it possible to monitor a much larger area with a greater level of detail. Grazing creates heterogeneity because sward structure

is, at the same time, both a cause and a consequence of grazing. Therefore, heterogeneity needs to be monitored, thus offering opportunity to multi-temporal UAS remote sensing to identify sward heights distribution across the paddocks for actual management. This monitoring has been simulated in Italian ryegrass pastures continuously stocked by sheep (Freitas and Lima (pers. comm.). At the bite level, the ideal sward structure in terms of STIR is 18 cm, so the pasture was monitored to maintain sward heights between 12 and 18 cm as grazing targets for the *rotatinuous* stocking, the concept of grazing management that aims at offering ideal sward structures to the grazing animal explained before (Carvalho *et al*., 2013). Areas of the paddock with less than 12 cm were specifically deferred until monitoring indicated sward height was recovered to targeted range. In areas higher than 18 cm, animals were concentrated with electric fences until sward height of that zone was controlled. On the average of the entire grazing period, this management interventions were successful to offer almost constantly more than 30% of the area with ideal sward structures. This is an example of how UAS-based monitoring of pasture height could empower flexibility and innovation in grazing management.

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# Remote sensing for grassland quality assessment: Status and Prospects

Astor T.[1] and Geipel J.[2]

*[1]Grassland Science and Renewable Plant Resources, Universität Kassel, Steinstrasse 19, 37213 Witzenhausen, Germany; [2]Department of Agricultural Technology and System Analysis, Norwegian Institute of Bioeconomy Research (NIBIO), Pb 115, 1431 Ås, Norway*

## Abstract

Grassland farmers face ever increasing demands on their production systems and the quality of their grassland yields. Estimating pasture quality using traditional field methods is limited as it is time consuming and costly, and requires some destructive sampling. The field of remote sensing offers alternative tools and techniques to overcome some of the limitations and thereby help farmers to receive spatial continuous and near real-time information about grassland quality parameters. This review gives an overview about recent developments in the remote sensing-based estimation of three aspects of grassland quality: feed quality, biological nitrogen fixation by legumes, and the identification of unwanted plant species.

**Keywords:** review, CP, ADF, legumes, invasive species, weeds

## Introduction

Economic, environmental and social drivers are causing major changes for farming systems in Europe. On the one hand, products (e.g. food) delivered by farmers must fulfil increasingly greater quality criteria including health, safety and quality. On the other hand, economic constraints due to increasing demands by the market, community, or government, limit the financial benefits available to farmers (van der Ploeg, 2020). One example is the Nitrates Directive (91/676/EEC) that demands that grassland farmers reduce nitrate leaching to groundwater by minimizing the application of fertilizer.

Up to 40% of the global land surface area (Blair *et al*., 2014) is covered by grasslands, and about 20% of the global soil organic carbon is stored in grassland soils (Conant, 2010). Almost 35% of the utilized agricultural land in the European Union is used for, or its use is related to, fodder production (i.e. permanent grassland, forage crops) (Huyghe *et al*., 2014). Not only is the spatial distribution of managed grassland areas in Europe highly variable, but also its environmental conditions and management strategies. In consequence, the variability and expectations of grassland quality are very diverse.

Perspectives on grassland quality can be manifold and they depend strongly on the aims and anticipated use of the grassland biomass. For fodder production, the protein and fibre content are of high importance (Wijesingha *et al*., 2020b), but for grazed extensive grasslands the presence of species that are poisonous or that have morphological structures to deter grazing (e.g. thorns) can be additional quality criteria (Lam *et al.*, 2020). From a nature conservation point of view, the species composition and diversity or seeding time of rare species can also be an important quality criterion of grasslands (Moeckel *et al*., 2016). Further, for bioenergy production the quality can be essential for the evaluation of grassland biomass (Joseph *et al*., 2018).

Estimating grassland quality in the field is a challenging task and traditional field methods are often labour and cost intensive. Commonly, farmers take representative biomass samples and use chemical analysis or lab-based near infrared spectroscopy (NIRS) to retrieve correct information about the protein and fibre content. These measurements cannot, of course, be made at frequent time intervals within a growing period, nor in a spatially continuous way, thus limiting the validity of the results for entire field sites. Remote sensing offers tools and sensors which could allow grassland managers to receive information about grassland quality in a spatially continuous, repeatable and comprehensible way (Wachendorf *et al*., 2017). However, while lab spectrometry (i.e. NIRS), and proximal remote sensing has shown potential to reduce the effort of expensive chemical lab analysis (Biewer *et al*., 2009; Pullanagari *et al*., 2012), the application of such methods on large areas and the time efficiency are limited. Existing and future satellite missions (e.g. European Sentinel satellite missions, EnMap) as well as airborne remote sensing systems show great potential to overcome these limitations (Raab *et al*., 2020; Wijesingha *et al*., 2020b).

This article focuses on the current state of remote sensing-based estimation of grassland quality parameters important for feeding farm animals. It is split into three sections. The first section deals with feeding quality (i.e. nitrogen and fibre concentration), the second section focuses on the estimation of biological nitrogen fixation by legumes, and the third section provides an overview of the identification of unwanted species (i.e. invasive and weed species) in grasslands.

## Feed quality

The quality of fodder can be described in terms of its biomass composition and available nutrients in relation to animal dietary requirements. It comprises nitrogen (N) (often expressed as crude protein (CP)), fibre content (acid detergent fibre (ADF) and neutral detergent fibre (NDF)), lipids, vitamins, macro- and micro-elements, and energy (Waghorn and Clark, 2004). Deriving information about grassland quality from canopy reflectance information has a rather short history and ranges from small scale (i.e. point measurements) (Biewer *et al*., 2009) to large scale (i.e. areal measurements) (Wijesingha *et al*., 2020b) studies. While empirical canopy reflectance-based prediction models have been developed for individual parameters like N, CP, ADF and NDF (Wijesingha *et al*., 2020b; Biewer *et al*., 2009; Safari *et al*., 2016; Capolupo *et al*., 2015; Näsi *et al*., 2018; Oliveira *et al*., 2020, Geipel *et al*., 2021), the relationship between other quality parameters and canopy reflectance have been less well examined. Common to all empirical models is the low generalizability of the results. As the quality of grasslands is affected by many different factors including species composition, management, environment and climate, the canopy reflectance varies between different sites. Consequently, there is a need for more generalizable models covering grasslands from different environments and management strategies that can potentially be applied, or by through less effort be adapted to new grassland sites. To the authors' knowledge, only one study has explored general empirical relationships between spectral reflectance pattern and nutritive values among different grassland sites (Wijesingha *et al*., 2020b). Using a hyperspectral full-frame camera mounted on an unmanned aerial vehicle (UAV), these authors collected spectral information (450-950 nm) at five different sites within Germany throughout a complete growing period. The management scheme of these sites ranged from intensively used grasslands with up to three cuts to extensively managed nature conservation grasslands. The data collection in each grassland site was conducted just before each cut. The two quality parameters of CP and ADF were predicted successfully using a machine learning approach and reached maximum accuracies of 89% for CP and 87% for ADF. The developed models were applied on all five sites to create information maps indicating the spatial distribution of the selected grassland quality parameters on a field level (Figure 1). This study did not only allow analysing the spatial variation of quality parameters at field scale but also temporal patterns and, thus, may serve for example to determine the effect of weather or climate changes on the nutritive value of grasslands. As an alternative to purely empirical approaches, the use of mechanistic modelling approaches, which are based on the radiative transfer theory, could enable relationships to be found between grassland quality parameters and spectral reflectance (Weiss *et al*., 2020). However, greater uncertainties and thus lower model accuracies are part of this approach.

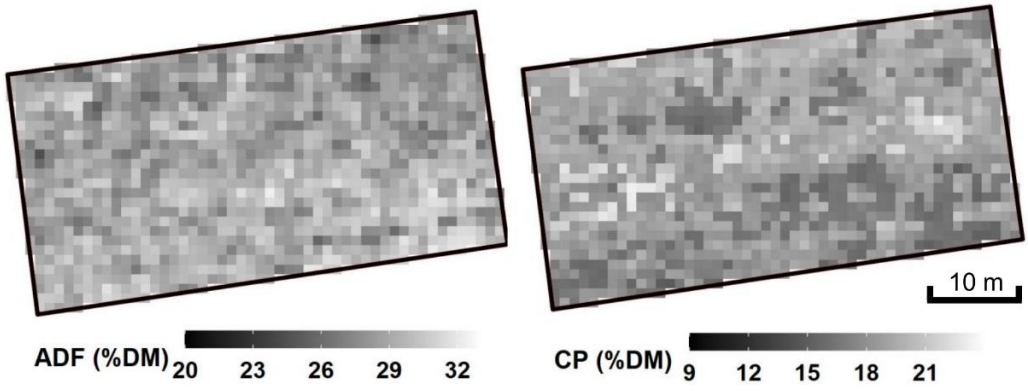


Figure 1. Prediction maps for crude protein (CP) (left) and acid detergent fibre (ADF) (right) for an intensively managed grassland site in Germany. The prediction model was created using hyperspectral data collected from five different sites with various management intensities. For more details, see Wijesingha *et al*. (2020b).

Moreover, existing the literature on remote sensing-based estimation of grassland quality show a strong geographic bias of the study sites towards the USA and South Africa (Astor *et al*., 2020), which further limits the explanatory power and generalizability of the suggested approaches and results under European conditions.

## Biological Nitrogen fixation

Another important quality parameter is the amount of N-fixing species (i.e. legumes) in the grassland composition. Legumes play an important role in the N cycle at the farm level, particularly in organic agriculture where the use of fertilizers is limited to organic fertilizer. Legumes will also receive more attention in conventional agriculture, as the nitrogen emissions on all farms must not exceed maximum thresholds set according to European rules. These restrictions will make legume-grass swards an important element of a farm's crop rotation cycle. Beside N acquisition, swards based on legume-grass mixtures provide additional positive effects on the subsequent cash crop, i.e. enhanced product quality and soil fertility as well as weed suppression. Besides the spatial complexity of legume-grass swards due to varying composition of species mixture, the N-fixing ($N_{Fix}$) ability also varies between years. To the authors' knowledge, Grüner *et al*. (2021) is the only study so far that has attempted to predict $N_{Fix}$ using UAV-based spectral reflectance and 3D-structure information from a terrestrial laser scanner (TLS) along a two-year growing period. The models achieved a high prediction accuracy of 14% for a model including both growing periods and two different grass-legume mixtures (i.e. clover-grass, lucerne-grass) (Grüner *et al*., 2021). The total accumulated predicted amount of $N_{Fix}$ was overestimated in comparison to the reference values by about 14 and 10 kg $ha^{-1}$ for the clover-grass and lucerne-grass mixture, respectively (Grüner *et al*., 2020). Although the results are promising, the generalizability as well as the interpretation of the models must be considered with care.

## Weeds and other unwanted species

Unwanted weed species like broad-leaved dock (*Rumex obtusifolius*) are often highly competitive and can decrease grass yield (Foster, 1989) and reduce forage quality by the presence of constituents like oxalic acid (Hejduk and Doležal, 2011). Another problem arises from non-native species invading grasslands, for instance the large-leaved lupin (*Lupinus polyphyllus*) which not only massively change the species composition of grasslands (Hansen *et al*., 2020), but also reduce the grassland quality, as such species may be poisonous for grazing animals. Normally, these unwanted species are controlled by chemical or mechanical weeding. Nevertheless, these treatments lead to several problems: a) the identification of exact location of the species is often performed manually, thus being labour and cost intensive, and b) the monitoring of the success of these treatments is cumbersome for large areas. For identifying and monitoring the distribution of unwanted species in grasslands, remote sensing offers suitable tools. The recent development of UAV technology allows imagery to be collected at adequately high spatial resolutions to identify even small weed species successfully. The utilized sensor systems are usually simple RGB cameras (Lam *et al*., 2020), but also more sophisticated spectral and thermal sensors may be suitable (Wijesingha *et al*., 2020a). Lam *et al*. (2020) successfully proved that it is possible to identify *R. obtusifolius* in native grasslands using an RGB camera and open-source image analysis tools. The reported classification accuracies are comparable to those of a manual field-based identification, showing the potential of the suggested approach for saving time, labour, and costs. The combination of complementary sensor systems may also improve prediction models for grassland parameters. So far, there has been a strong focus on yield estimations.

Nevertheless, sensor fusion has also shown very good results for the identification of invasive species; for instance, Wijesingha *et al*. (2020a) used a combination of RGB and thermal information to successfully identify *L. polyphyllus* at two extensive grassland sites. The authors report a very high correlation between automated and manual image analysis (i.e. traditional method) (Figure 2). Considering the decreasing costs for UAV-borne cameras, simultaneously collecting visual and thermal information, the presented examples show the great potential of UAV remote sensing for species mapping in grasslands.

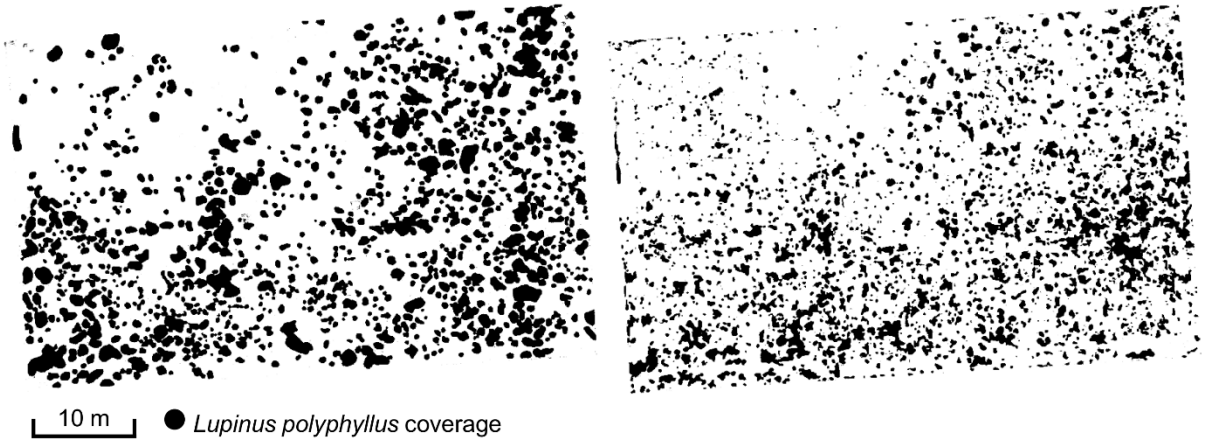


Figure 2. Lupin coverage (black) map for a mountain hay meadow at the peak biomass (12 June 2019). Left: Lupin coverage was digitized manually (traditional method). Right: Lupin coverage was semi-automatically digitized using an object-based image analysed and RGB as well as thermal information.

## Conclusions

Remote sensing offers suitable tools and approaches for predicting and mapping various aspects of grassland quality. However, the prediction accuracy and the generalizability of the developed models needs to be further improved. The recent technological development of sensors and sensor carriers (e.g. UAVs) makes it more likely that even people without specialized knowledge will be able to collect the necessary data. The data processing and analysis, on the other side, still requires expert knowledge and substantial computing resources, making professional support inevitable. Nevertheless, with the expected increase in remote sensing service providers in the agricultural domain, the proposed remote sensing technology is likely to reach practical applicability soon. For successfully bridging the gap between scientific research and practical application a good exchange of knowledge and mutual acceptance is needed.

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# Estimating biomass yield and growth response to temperature in red clover using terrestrial laser scanning

Kronenberg L.[1,2], Srirangaraj J.[1,2], Kirchgessner N.[1], Knorst V.[2], Grieder C.[3], Walter A.[1], Studer B.[2] and Kölliker R.[2]

*[1]Crop Science, Institute of Agricultural Sciences, ETH Zurich, CH-8092 Zurich; [2]Molecular Plant Breeding, Institute of Agricultural Sciences, ETH Zurich, CH-8092 Zurich; [3]Fodder Crop Breeding, Agroscope, CH-8046 Zurich*

## Abstract

Due to its high protein content, good digestibility and its ability to fix atmospheric nitrogen, red clover (*Trifolium pratense* L.) is an important forage crop in temperate livestock production systems. Increased yield and improved adaptation of red clover would increase Europe's self-sufficiency in high quality fodder protein. The aim of this study was to assess growth dynamics and their relation to yield and flowering time in a set of 395 European red clover accessions using a high throughput field phenotyping approach. Terrestrial laser scanning implemented on the ETH field phenotyping platform (FIP) was used to track canopy height increase in high temporal resolution. Canopy height was highly heritable before the second cut ($H^2$= 0.93) and was predictive for biomass yield with an accuracy of $R^2$= 0.88. However, heritability of canopy height and predictability of biomass decreased in later cuts. Regressing short term growth rates against ambient temperature revealed a highly heritable ($H^2$= 0.89) genotype-specific growth response to temperature. Genotypes with a higher temperature response showed increased yield and earlier flowering. We conclude that high throughput canopy height measurements, i.e. using terrestrial laser scanning, can be applied to estimate biomass yield as well as growth response to temperature in red clover.

**Keywords:** LiDAR, canopy height, biomass, temperature

## Introduction

Beef and dairy production in Europe relies heavily on imported soybean meal as a protein source in the diet. This is associated with negative environmental impacts and competition for the use of arable land between human food and animal feed production. Due to their high nutritive value and symbiotic fixation of atmospheric N, increased use of legume-grass swards offers a more sustainable feed source and reduce Europe's protein dependency (Lüscher *et al*., 2014). With its high yield potential, protein content and nutritional value, red clover (*Trifolium pratense* L.) is among the most important forage legumes in temperate climates (Boller *et al*., 2010). In perennial mixtures, it is an important component facilitating good establishment and early yield (Suter *et al*., 2014). Forage yield and persistence are among the main breeding objectives in red clover (Boller *et al*., 2010). High throughput field phenotyping facilitates the assessment of large numbers of genotypes in high temporal resolution and thus enables the quantification of genotype by environment interactions (Cendrero-Mateo *et al*., 2017). It was recently shown that remote estimation of canopy height can be used to predict biomass in clover species (Grüner *et al*., 2019; Roth and Streit, 2018) and that height development is related to phenology and temperature response in wheat (Kronenberg *et al*., 2021; 2017). The aim of this study was to assess height growth dynamics in a diverse set of European red clover accessions and investigate their relation to yield and flowering time.

## Materials and methods

A three-year field experiment (2018-20) comprising 395 European red clover accessions was conducted in the ETH field phenotyping platform FIP (Kirchgessner *et al*., 2016). The experiment was sown in an augmented design using two-row microplots. In 2018, the trial was left undisturbed except for husbandry measures to enable good establishment of the crop. In 2019, the crop was cut four times. At cuts 2-4, biomass of a subset (n=111, 102, 102; respectively) of the plots was recorded. After the first cut, canopy height was measured 1-2 times weekly using terrestrial laser scanning (Friedli *et al*., 2016) implemented on the FIP (Kronenberg *et al*., 2017). From these data, growth rates were calculated and regressed against ambient temperature to extract a genotype specific, temperature mediated growth component

(slp[GR~T]; i.e. the slope of the linear regression) following Kronenberg *et al.* (2021). Flowering time was recorded in 2019 and 2020 for each plot according to BBCH, as day of year when 50% of plants were in bloom (Lancashire *et al*., 1991). Persistence was evaluated before the third and fourth cut in 2019 and again after winter in 2020 as percentage of red clover in each plot. For the statistical correction for spatial effects, extraction of adjusted genotype means and calculation of heritability ($H^2$), a linear model framework including p-splines was used (for details see Rodríguez-Álvarez *et al*., 2018).

## Results and discussion

The diverse geographical background of the population became apparent in the evaluation of flowering time. In 2019, only 50% of the genotypes had reached flowering by the time of the first cut, which was unexpected. Thus, only flowering data of 2020 could be evaluated, since no height and yield evaluations were done then, and the first cut could thus be postponed. Flowering time in the population ranged from 120 to 179 days after January 1st and had a heritability of 0.76. A total of 20 accessions did not reach flowering at all.

A consistent increase in canopy height over time was observed for all three investigated growth cycles (Figure 1a). At the second and third cut, average canopy height reached 0.4 m and $H^2$ was *0.93* and *0.82*, respectively (Figure 1b). In the last growth cycle, towards the end of the vegetation period, canopy height increase was much slower compared to the first two cycles and heritability of canopy height decreased towards 0.42 at the last cut. A log-linear model was used to estimate biomass based on the canopy height at harvest (Figure 1c). At the second cut, the model showed a high predictive accuracy ($R^2$ = *0.88*) which is in accordance with previous studies using similar approaches (Grüner *et al*., 2019; Roth and Streit, 2018). However, the model performance decreased drastically for the third and the fourth cuts. This, together with the decreasing heritability of height may be due to progressing suppression of red clover in the experiment, mainly by white clover. This is seen in persistence, which decreased from 78% ($H^2$ = *0.66*) to 59% ($H^2$ = *0.65*) and 48% ($H^2$ = *0.66*) from the first to the third rating. The temperature-related growth parameter slp[GR~T] was highly heritable ($H^2$ = *0.89*) and positively correlated with yield and persistence (Fig. 1d). All these traits were negatively correlated with flowering time. Stem length and early flowering have previously been associated with higher persistence in red clover (Ford and Barrett, 2011; Herrmann *et al*., 2008). Our results indicate that higher persistence, yield and earlier flowering are further associated with a genotype specific, temperature mediated growth.

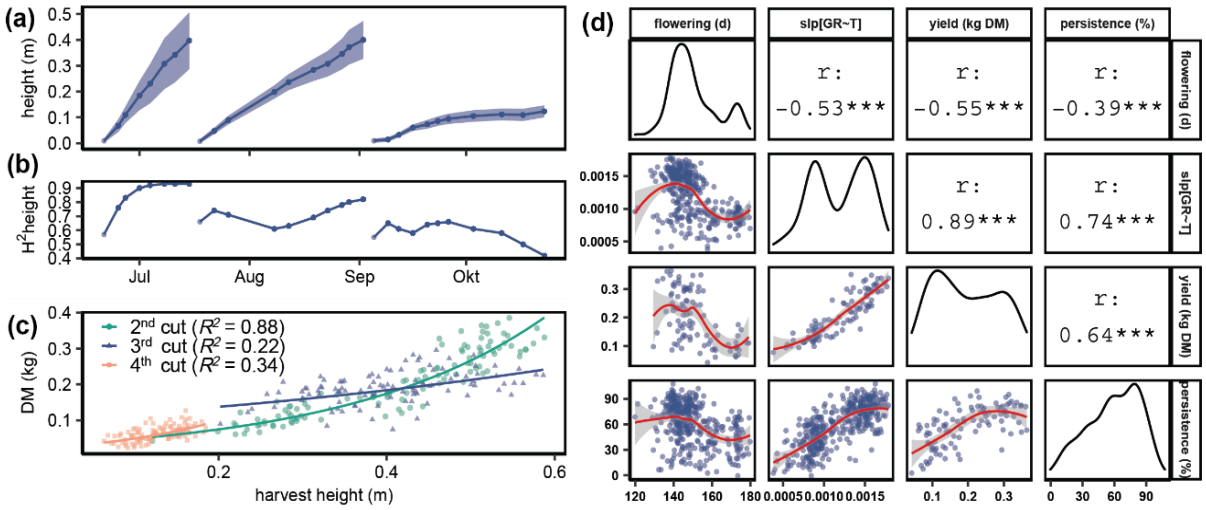


Figure 1: (a) Canopy height development after the first cut in 2019 showing the adjusted mean (dots) ± standard deviation (shaded area) of the 395 accessions and (b) heritability at the respective measurement timepoints. (c) Log-linear regression between dry matter yield (DM) and harvest height for cuts 2-4. (d) Pearson correlations including scatterplots and loess curves between flowering time, temperature response (slp[GR~T]), dry matter yield (only second cut) and persistence, as well as distributions of the respective traits.

## Conclusions

Here, we demonstrated that canopy height measurements may be used to estimate biomass yield in red clover. Furthermore, our data suggest that measurements in high temporal resolution enable the extraction of heritable environmental response traits such as temperature mediated growth.

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# Using commercial field spectrometers for estimating digestibility of grasslands: an example with the Yara-N sensor

Morel J.[1], Zhou Z.[1,2] and Parsons D.[1]

*[1]Swedish University of Agricultural Sciences, Department of Agricultural Research for Northern Sweden, Umeå, Sweden; [2]Zhejiang University, College of Biosystems Engineering & Food Science, Hangzhou, China*

## Abstract

Mixed ley farming largely dominates the agricultural landscape of northern Sweden and leys are the major source of feed for dairy cattle. Forage digestibility is the main criterion that determines the optimal harvest date. Developing a real time and accurate tool to estimate the digestibility would increase the efficiency of the whole dairy sector. We tested how a commercially available field spectrometer (Yara N-Sensor, Yara) could be used for such a purpose. Data were collected from experimental plots with various rates of nitrogen fertilization and timothy and red clover ratios across three field seasons (2017 to 2019) and four sites in northern Sweden. Spectral data were acquired for each plot before harvesting. Collected samples were analysed for in-vitro true digestibility (IVTD) using ANKOM procedures. Different regression techniques were applied to link the spectral data with the laboratory results. The results indicate good performances for the different models for estimating IVTD (*RMSE* = 12.9 to 16.8 $g.kg^{-1}$ and $R^2$ = 0.88 and 0.70 for support vector machines and partial least squares, respectively). These findings suggest there is a good potential for field spectrometers such as the Yara N-Sensor for real time monitoring of digestibility.

**Keywords:** field spectrometry, in-vitro true digestibility, leys

## Introduction

Forage crops, predominantly leys, contribute a large part of the ruminant feed requirements in Northern latitudes. As a consequence, the productivity and quality of leys affects the economic efficiency of meat and dairy production. Information on digestibility of the ley is important for farmers to decide on the best harvest window, as this may eventually increase the meat and milk production per animal. At present, the estimation of the digestibility is performed in the lab using either traditional wet chemistry analyses or near-infrared spectrometry. Lab analysis, though accurate and robust, is time-consuming, while farmers need almost-immediate information to schedule their harvest efficiently. Consequently, a tool that performs near-real time estimation of digestibility would help the farmer to plan his harvest and result in an improvement of the efficiency of production, from the field to the animal. In recent years, field spectrometers have become increasingly used both in research and industry. These sensors capture the information carried by vegetation-reflected light that can ultimately be used to evaluate traits of the vegetation. Recent solutions have been developed using field sensors to evaluate the vigour of crops (Zhang *et al.*, 2014), their biomass production (Vescovo *et al.*, 2012) or nitrogen uptake (Zhou *et al.*, 2019).

Among these, the Yara-N sensor (YNS) is an already a commercial tool and is mostly used to assess nitrogen needs of cereal crops. As a consequence, a YNS-based tool for adjusting fertilisation rates from sensor-estimated botanical composition could easily be implemented at an industrial level, as the sensor is already widely used by farmers in Nordic countries.

Therefore, the main objective of this work is to develop mathematical models that would link the spectral information acquired with a YNS to a lab-determined digestibility, defined here as the in-vitro true digestibility (IVTD). A Partial Least Square Regression (PLSR) and a Support Vector Regression (SVR) model were adjusted and their respective performances to estimate the botanical composition were assessed using statistical indicators.

## Materials and methods

A total of 337 samples were taken at Lännäs, Ås, Röbäcksdalen and Öjebyn (Northern Sweden) during the 2017 to 2019 field seasons on experimental plots and production fields with mixtures of grass

(timothy, *Phleum pratense* L.) and legume (red clover, *Trifolium pratense* L.). Sample spots included various nitrogen fertilisation rates and botanical compositions. For each sample spot, a circular sampling frame of 50 cm diameter was used to delineate the sample area. Canopy spectral measurements were performed close to solar noon on clear sky days, with a zenithal viewing angle of 45° using a YNS spectrometer (Yara International ASA, Oslo, Norway) before harvesting the sample. The sensor was held at a constant height of 0.86 m above the ground, while the sampling frame was placed on the ground, 0.55 m from the sensor so that the area measured by the sensor would approximately match with the sampling area. Acquired spectra contained 60 bands ranging from 400 to 1000 nm, with a spectral resolution of 10 nm and a field of view of 25°. The solar irradiance was measured simultaneously using an external sensor and used to convert the spectral raw measurements to reflectance. Samples were cut at 7 cm above the ground level and hand separated into grass and legume fractions. Sub-samples were then oven-dried at 70 °C for 48 h until they reached a constant weight and analysed for In Vitro True Digestibility (IVTD) using ANKOM procedures described by Valentine *et al.*, (2019) using the Daisy II 200/220 incubator (ANKOM Technology, Fairport, NY). Samples were incubated in F57 ANKOM digestion bags for 48 h at 39°C. Two chemometric models were calibrated to estimate the botanical composition of the samples using the canopy spectral reflectance (CSR), namely a Partial Least Square Regression (PLSR) and a Support Vector Regression (SVR). All analyses were performed using R 4.0.2 (R Core Team, 2020), and SVR and PLSR models were built using the liquidsvm and pls packages, respectively. For both models, a leave-one-out cross validation was used, as no validation dataset was available for a regular calibration-validation procedure. A radial-basis kernel was used with SVR to account for the potential non-linear relationship between the botanical composition and the spectral data. Models were evaluated using the root mean squared error (*RMSE*) and the coefficient of determination ($R^2$).

## Results and discussion

Both PLSR and SVR models showed relatively good performances for estimating the IVTD. If considering the slope of regressions (Figure 1), PLSR tended to perform better than SVR, with slopes equal to 0.93 and 1.32, respectively. However, SVR tended to outperform PLSR both in terms of *RMSE* (12.9 and 16.8 $g.kg_{DM}^{-1}$ for SVR and PLSR, respectively) and $R^2$ (0.88 and 0.7 for SVR and PLSR, respectively). A trend of non-linearity can be observed between 800 and 850 $g.kg_{DM}^{-1}$, for both models.

The important regions of the light spectrum for estimating the nutritional quality of forages is located into the short wave infrared range (1400 – 2400 nm, Norris *et al.*, 1976). Although the light information used was acquired between 400 and 1000 nm, we obtained reasonable accuracies for estimating IVTD. This can be due to the fact that IVTD is inversely related to the biomass, which can be estimated using the near-infrared light information.

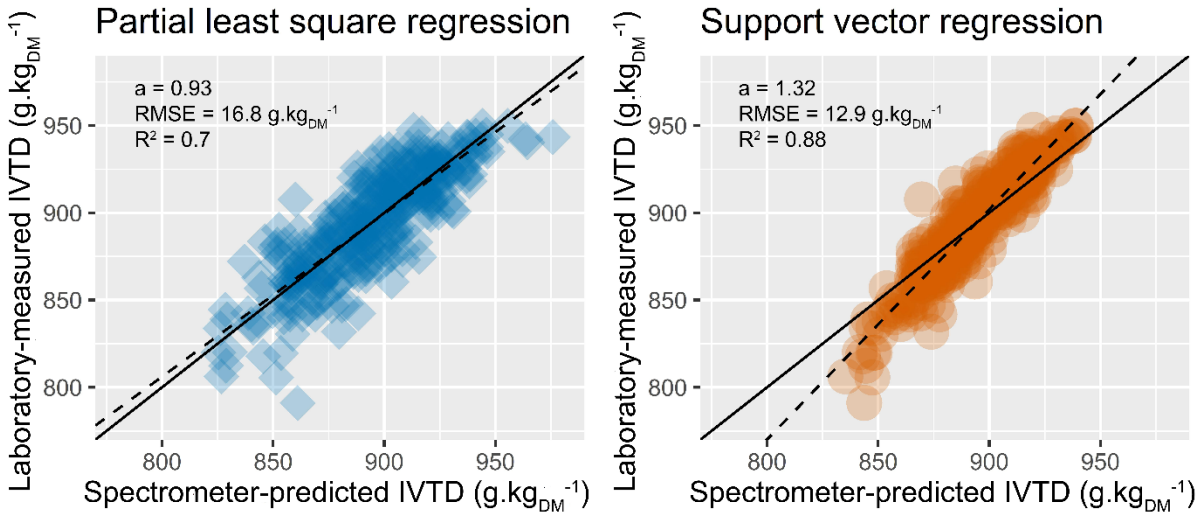


Figure 1. Spectrometer-predicted vs laboratory-measured in-vitro true digestibility for PLSR and SVR. The dashed lines indicate the linear regressions, the black lines indicate the 1:1 lines, and a represents slope.

## Conclusions

This work showed the potential of the Yara-N sensor for on-field estimations of the in-vitro true digestibility of leys. Support vector-based regressions tend to perform better than partial least square regressions. If confirmed, these results could be used develop a practical tool to help farmers to estimate the best harvest window.


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# Evaluation of remote sensing vegetation indices to estimate forage yield and quality of different fertilized grassland

Schaumberger A., Klingler A. and Schweiger M.

*Agricultural Research and Education Centre (AREC) Raumberg-Gumpenstein, 8952 Irdning-Donnersbachtal, Austria*

## Abstract

As many studies show, spectral signatures provide detailed information on plant functional traits. Forage yield and quality are of great importance in grassland management. Therefore, we derived widely used vegetation indices from hyperspectral reflectance data and evaluated their potential for estimating yield and quality on grassland plots with different fertilization. The spectral reflectance measurements were carried out shortly before each of three harvests per year with a field spectrometer on a long-term experiment with 24 organic and mineral fertilization treatments with a four-fold repetition. Starting with a null model, the best predictors for dry matter yield (DM, kg $ha^{-1}$) and crude protein content (CP, g $kg^{-1}$) estimation were determined from selected vegetation, chlorophyll and water indices and a leaf area index using an exhaustive search algorithm on a training data set. The estimation of DM with an index combination on an independent test data set yielded $R^2 = 0.76$, the CP was estimated with $R^2 = 0.69$. Additionally, we compared the index-based results with neural net analyses using Sentinel-2 bands calculated with spectral response functions (S2-SRF) as predictors. With a variety of observations, we have shown that simple indices can differentiate forage yield and quality on grasslands evolved under different levels of nutritional supply.

**Keywords:** spectral signatures, grassland yield, forage quality, Sentinel-2

## Introduction

The great diversity of land use types and management intensities in grassland with very different plant communities is a big challenge for empirical and dynamic grassland models. As Reinermann *et al.* (2020) show in their overview, remote sensing with multi- and hyperspectral reflectance data offers a wide range of possibilities to get traits of plant stands, which represent the effects of site and management factors. Sensors on several platforms ranging from terrestrial systems like field spectrometers to UAVs and satellites are used for this purpose, supporting different spatial scales from field to global applications.

In this study, the potential of remote sensing vegetation indices was analysed by combining and verifying them for yield and quality estimates of highly diverse grasslands. These models were compared with an approach using the S2-SRF transformed Sentinel-2 bands (Klingler *et al.,* 2020) to show differences in using indices and original spectral information. Based on Sentinel-2 bands, models can be used in image-based applications on a large spatial scale.

## Materials and methods

The evaluation of vegetation indices for estimating grassland yield and quality is based on hyperspectral data collected by the HandySpec Field VIS/NIR 1.7 (tec5) field spectrometer with a range from 400 to 1690 nm. The spectral measurements were taken on a long-term field fertilization experiment, established in 1946 in Admont (Styria, Austria) three times a year, immediately before each cut between 2015 and 2019.

The field experiment consists of 96 plots and shows a wide variability of well-established plant stands that have developed very differently over more than 70 years due to 24 continuous fertilization treatments, each repeated four times. Besides an unfertilized treatment, the other plots are supplied with mineral (N, P, K) and organic fertilizers (solid and liquid manure) in different combinations and levels.

From the obtained spectral signatures we calculated commonly used vegetation indices (NDVI, RVI, SAVI, EVI, RDVI, TVI, MTVI1 MTVI2, CARI, LCI, GI, PRI, REIP1, REIP2, LWVI1, LWVI2, NDNI, TGI (definitions see at indexdatabase.de)) and the Leaf Area Index (LAI). As described by Klingler *et al.*

(2020), we converted hyperspectral data into the corresponding Sentinel-2 bands using the S2-SRF (ESA, 2018) and we applied algorithms proposed by Baret *et al.* (2010) in combination with radiative transfer models for LAI calculation. We selected the indices with the highest prediction power for DM and CP using an exhaustive search algorithm on a training data set in R. Furthermore, we compared linear models (LM) based on the selected indices with an Averaged Neural Network (ANN) from the R package caret (Kuhn, 2008) were the S2-SRF bands B2, B3, B4, B5, B6, B7, B8, B8a, B11, and B12 were used as predictors. We split the data for both models in two different ways: i) a random split into 2/3 for training and 1/3 for the test, and ii) a split by years with 2015, 2016 and 2017 as a training set and 2018 and 2019 as a test set for the DM model and 2015 and 2016 as a training set and 2017 as a test set for the CP model (CP analyses were only available for three years). We optimized the model parameters using the R function "trainControl" for the training data set and evaluated the models by calculating $R^2$ and RMSE on the independent test data set.

## Results and discussion

Among the calculated indices and all their combinations, the Leaf Water Vegetation Index 2 (LWVI2) (Galvão *et al*., 2005), a variant of the Normalised Difference Water Index (NDWI) in combination with the Normalised Difference Nitrogen Index (NDNI) (Serrano *et al*., 2002) provided the best estimation results for grassland yield. The best correlation between modelled and observed CP as a quality parameter was given in the combination of LWVI2 and LAI. Both results are shown in Figure 1.

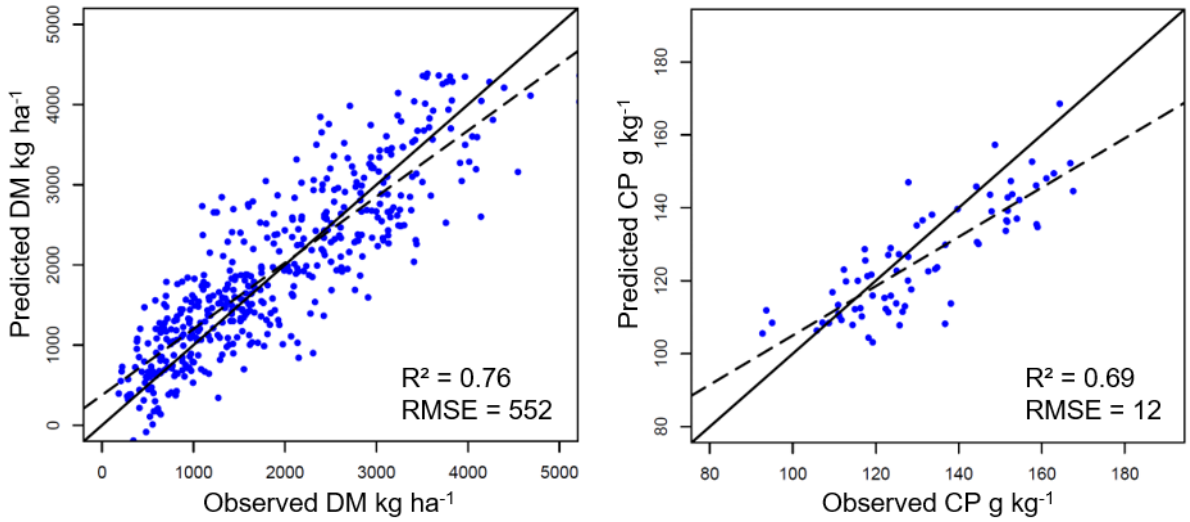


Figure 1. Estimation of DM and CP by a linear model using a random test dataset with LWVI2 & NDNI for DM and LWVI2 & LAI for CP.

The results of the ANN model with S2-SRF data are shown in Table 1 and can be compared there with the index-based results. The $R^2$ as well as the RMSE of both modelling approaches, are in a comparable range.

Table 1. Comparison of $R^2$ and RMSE results for randomly and yearly split test datasets, from a linear model (LM) with combination of two different indices and an Averaged Neural Network (ANN) using S2-SRF bands.

| | | Random split | | | | Split by years | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | LM (2 Indices) | | ANN (S2-SRF) | | LM (2 Indices) | | ANN (S2-SRF) | |
| | n | $R^2$ | RMSE | $R^2$ | RMSE | $R^2$ | RMSE | $R^2$ | RMSE |
| Dry Matter kg $ha^{-1}$ | 1438 | 0.76* | 552* | 0.79 | 511 | 0.65 | 598 | 0.60 | 645 |
| Crude Protein g $kg^{-1}$ | 360 | 0.69* | 12* | 0.74 | 10 | 0.71 | 13 | 0.72 | 11 |

* Results are plotted in Figure 1

By combining two indices, we are already using those parts of the electromagnetic spectrum that contribute most to the estimate. Therefore, extending the model to include all S2-SRF bands does not add much value. However, the direct use of Sentinel-2 bands supports a large-scale application.

To verify the model results, a data split is used in two ways. While a random split does not distinguish between replicates or survey years, a split by years applies the test to independent data from an entire year. This demonstrates the prediction power of each model for all three growths of an independent year.

## Conclusions

The combination of remote sensing vegetation indices supports considerable estimates of yield and forage quality. We found that directly used multispectral data in neural networks achieve similar prediction accuracy as indices. For further development of the models, other predictors should be added, and the ground truth database needs to be extended to other sites and climate regions.

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# Information on yield proportion of grasses slightly improves the estimate of dry matter yield based on LAI

Peratoner G., Mairhofer F., Zwack B. and Matteazzi A.

*Laimburg Research Centre, Vadena/Pfatten, I-39040 Ora/Auer, Italy*

## Abstract

Grassland yield estimates from remote sensing often rely on Leaf Area Index (LAI) or LAI-derived variables. We hypothesize that LAI may saturate at high yield levels resulting in inaccurate estimates due to plant parts contributing more to yield than to LAI, such as the stems. In a multi-site field experiment studying the effects of organic fertilization on the vegetation of moderately species-rich mountain permanent meadows, we measured dry matter yield, Leaf Area Index (with the sensor AccuPAR LP-80) and the yield proportion of grasses, legumes and forbs at the time of the first cut over three growing seasons. We evaluated the effect of the yield proportion of grasses, which were expected to provide the most relevant contribution of non-leafy plant material, on the accuracy of predicting dry matter yield by means of a linear mixed models accounting for LAI and design factors (site, year and site x year). Including the yield proportion of grasses into the statistical model allowed to slightly improve the accuracy of the prediction from 0.615 to 0.635 $R^2$.

**Keywords:** permanent meadows, LAI, grassland yield, botanical composition

## Introduction

Leaf Area Index (LAI) and other indices derived from it are important tools for assessing grassland growth and monitoring the variation of its productivity by means of remote sensing data (Roumiguié *et al.*, 2015; Klingler *et al.*, 2020a). As the dry matter (DM) accumulation during the first growth cycle is boosted by the generative development (especially of grasses) starting with stem elongation and by a shift of the leaf-to-stem ratio towards an increased proportion of stems, we hypothesized that LAI may progressively underestimate forage yield at later developmental stages of permanent meadows because of the increasing proportion of non-leafy plant material contributing more to the yield than to LAI. To this aim, we evaluated the effect of the yield proportion of grasses on a LAI-based estimate of forage DM yield, as grasses are expected to provide the most relevant contribution of non-leafy plant material.

## Materials and methods

The data were collected just before the first cut in 2018, 2019 and 2020 at a multi-site grassland experiment in the mountain area of South Tyrol (NE Italy), investigating the effect of organic fertilization on the botanical composition and forage production of moderately species-rich mountain permanent meadows. The measurements were performed at six sites covering a wide range of topographic features and harvest dates (Table 1). Each site included 9 plots of 5 x 5 m. Three of them were control plots and the other six were subjected to fertilization treatments, being combinations of different cattle manure type (slurry/farmyard manure/farmyard manure + liquid manure) and different fertilization levels (equivalent of a total N-input of 55.5/110 kg $ha^{-1}$). Harvesting occurred in accordance with the mowing dates adopted by the farmers for their own grassland surrounding the experimental fields. LAI was indirectly estimated from simultaneous measurements of the photosynthetically active radiation below and above canopy performed by means of the linear sensor AccuPAR LP-80 (Decagon Devices Inc., Pullmann, USA). Measurements were made inserting the sensor bar parallel to the ground at eight randomly chosen spots within each plot (two from each side). The above canopy sensor was aligned according to the slope inclination of each plot. The leaf area distribution parameter was kept equal for all communities. Afterwards, the yield proportion of grasses, legumes and forbs was measured by the point quadrat method (Peratoner and Pötsch, 2019) in three of nine plots per site by lowering a metal rod at 80 points per plot spaced 10 cm apart (20 along each plot side, 25 cm from the plot margin) and recording every plant contact. The yield proportion was computed as the percentage of contacts of each functional group with respect to the sum of all contacts. We made use of a wooden frame, the inclination of which was continuously adjusted to ensure the verticality of the measuring metal rods even on steep slopes. In the remaining plots, the yield proportion was visually estimated using the measured values

as a reference. Then, four forage samples were obtained in each plot within a 50 x 50 cm metal frame placed randomly along a diagonal by means of electric scissors at a stubble height of about 5 cm. The forage samples were then oven-dried at 60°C until weight constancy and weighed. For each sampling event, measurements within each plot were averaged prior to further statistical analysis, treating the plot as experimental unit. Data analysis was performed by multiple regression by means of mixed models. LAI and the yield proportion of grasses were treated as covariates and modelled by means of polynomial regression, whilst the design factors site, year and site x year were treated as random terms. Additionally, the plots were considered as subject of repeated measurements over years. The model accuracy was expressed as the squared correlation between observed and predicted values obtained with a five-fold cross-validation (Hawkins *et al.*, 2003) and was used for the stepwise forward model selection.

Table 1. Location and site characteristics of the experimental fields.

| Coordinates (N, E) | 46°42'33", 11°55'3" | 46°42'34", 11°55'5" | 46°44'47", 12°13'20" | 46°45'7", 12°12'28" | 46°35'6", 11°55'37" | 46°35'8", 11°55'36" |
|---|---|---|---|---|---|---|
| Altitude (m a.s.l.) | 1120 | 1110 | 1540 | 1710 | 1675 | 1695 |
| Aspect | WNW | WNW | SSE | S | S | SSW |
| Slope (°) | 6 | 17 | 18 | 10 | 13 | 24 |
| Cut frequency (cuts $yr^{-1}$) | 3 | 2 | 3 | 2 | 3 | 2 |
| Harvest date of first cut (range) | 31.05-07.06 | 27.06-07.07 | 08.06-21.06 | 26.06-07.07 | 12.06-22.06 | 11.07-18.07 |
| Plant species richness at trial start | 26.8 | 44.6 | 26.7 | 36.6 | 31.2 | 35.9 |

## Results and discussion

The DM yield of the first growth cycle ranged between 0.62 and 6.42 t $ha^{-1}$ (mean 2.77 t $ha^{-1}$), LAI ranged between 2.18 and 6.39 (mean 4.16) and the yield proportion of grasses ranged between 22.60 and 76.26% (mean 47.25%). The model accounting for LAI alone ($P < 0.001$) resulted in an $R^2$ of 0.615 and a *RMSE* of 0.64 (Figure 1a). The inclusion of the yield proportion of grasses into the previous model (both LAI and yield proportion of grasses with $P < 0.001$) resulted in a slight improvement of both $R^2$ (0.635) and *RMSE* (0.63) (Figure 1b) and shows that the expected yield increases both with LAI and grasses yield proportion. However, overestimation of low yields and underestimation of high yields were observed for both investigated models.

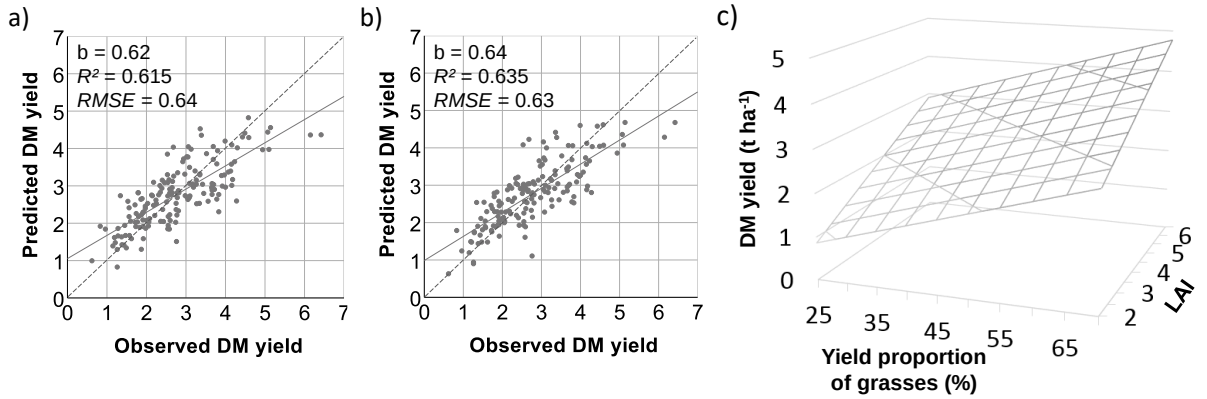


Figure 1. Observed vs. predicted DM yield based on a) LAI alone, on b) LAI and yield proportion of grasses and c) predicted yield values based on LAI and yield proportion of grasses. The dashed line is the 1:1 identity line, b is the regression slope.

The relationship of LAI and grass yield proportion with DM yield was best described by first degree polynomials; no significant interaction between LAI and grass yield proportion was detected. The relatively low $R^2$ values obtained are likely to be explained by the fact that most of the data were collected at a time relatively near to biomass peak. It must be also pointed out that the random design effects accounted for a large proportion of the total variation of the random part of the model (80.5% and 67.9%

for the baseline and the final model respectively). Indeed, LAI alone has been found elsewhere to be a poorer predictor of forage DM yield than compressed sward height measured by rising plate meter, but also to be able to effectively complement compressed sward height in estimating forage yield (Klingler *et al.*, 2020b). However, the underestimation of yield based on LAI may be even more pronounced for AccuPAR LP-80 than for other sensors, as its LAI estimates were shown to saturate slightly earlier at high LAI measured values (Klingler *et al*., 2020a).

## Conclusions

The results suggest that LAI measurements in the proximity of biomass peak of the first growth cycle of permanent meadows may result in an underestimation of forage yield at high yield levels and that this is partly caused by the proportion of grasses causing a shift of the leaf-to-stem ratio towards an increased proportion of stems. However, the accuracy improvement achieved by accounting for the yield proportion of grasses is very small.

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# Potential of Sentinel-2 and optimal hyperspectral configuration to assess forage quality in permanent grasslands of open woodlands; preliminary results

Fernández-Habas J.[1], Leal-Murillo J.R.[1], Hidalgo-Fernández M.T.[1], Gómez-Giráldez P.J.[2], González-Dugo M.P.[2], Milazzo F.[3] and Fernández-Rebollo P.[1]

*[1] Department of Forest Engineering, ETSIAM, University of Cordoba, Ctra. Madrid, Km 396. 14071 Córdoba, Spain; [2]IFAPA. Institute of Agricultural and Fisheries Research and Training of Andalusia. Avd. Menéndez Pidal s/n, 14071 Córdoba, Spain; [3] Department of Agronomy, Hydraulic Engineering Area, University of Cordoba, Spain*

## Abstract

We explored the capability of Sentinel-2 spectral configuration to assess crude protein (CP), neutral detergent fibre (NDF), acid detergent fibre (ADF) and enzyme digestibility of organic matter (EDOM) in open woodlands grasslands. Canopy reflectance measured with an ASD FieldSpec Spectroradiometer resampled to the configuration of Sentinel-2 MSI bands was used to calibrate models by Partial Least Squares Regression (PLSR). Models were tested over real Sentinel-2 data. The potential of hyperspectral configuration to assess forage quality was also investigated using PLSR and waveband selection procedure. Sentinel-2 based PLSR models showed a moderate predictive ability to assess CP with $R^2$=0.54 and Ratio of Prediction to Deviation (RPD) =1.55 while poor results ($R^2$<0.50 and RPD<1.50) were obtained for NDF, ADF and EDOM. 10 nm-resolution hyperspectral configuration allowed quantitative results of CP predictions.

**Keywords:** crude protein, PLSR, band selection, field spectroscopy

## Introduction

Remote sensing of grassland quality in open woodlands on farms might help to adjust stocking rates, and to organise grazing and feed supply at farm level (Ramoelo *et al*., 2018; Starks *et al*., 2006). Sentinel-2 configuration has shown potential to estimate forage quality. Raab *et al*. (2020) obtained $R^2$ values of 0.72 using Sentinel-2 data to predict crude protein. The use of field spectroscopy data to assess the potential of Sentinel-2 configuration to predict forage quality has been investigated and shows promising results (Lugassi *et al*., 2019; Ramoelo *et al*., 2015). The application of remote sensing to assess forage quality in highly diverse Mediterranean permanent grasslands of open woodlands has not received much attention. We investigated the potential of Sentinel-2 data to assess crude protein (CP), neutral detergent fibre (NDF), acid detergent fibre (ADF) and enzyme digestibility of organic matter (EDOM) by using a combination of simulated Sentinel-2 data from field spectroscopy and true Sentinel-2 imagery using Partial Least Squares Regression (PLSR). We also explored the potential of 10nm-resolution hyperspectral data to predict forage quality using PLSR and waveband selection from field spectroscopy data.

## Materials and methods

Two sampling campaigns were performed, during the growing seasons of 2012-13 and 2018-19, in open woodland farms located in the north of Andalusia (Spain). Pasture herbage within 0.40 x 0.40 m sampling quadrats was cut to ground level and then oven-dried for 48 h at 60ºC and ground for subsequent chemical analysis. In total 173 samples were collected, 125 from 2012-13 and 48 from 2018-19. Before cutting the pasture herbage in the sampling quadrats, canopy reflectance was recorded using an ASD FieldSpec FR Spectroradiometer (ASD Inc, Boulder, Colorado, USA) of 350-2,500 nm spectral range and 1 nm interpolated spectral resolution. Reflectance was recorded within the sampling quadrats before clipping the herbage, holding the fibre optic probe mounted on a pistol grip at 1.20 m height, resulting in a 0.22 $m^2$ recording area. The wavebands affected by atmospheric (1370-1410 nm and 1816-1941 nm) or instrumental noises (350-395 nm and 2300-2500 nm) were removed. The spectroradiometer data were then resampled to Sentinel-2 MSI channels (those having 10 and 20 m spatial resolution) and to 10 nm hyperspectral bands for their respective analyses. For the sampling campaign of 2018-19, 25 tree-free 20 x 20 m Sentinel-2 pixels were identified, and within the 10 x10 m

pixel most distant from the closest tree located in the ground, four sampling quadrats (0.4 x 0.4 m) were set. The four samples were averaged to obtain a representative value of each pixel. These 10 x10m plots were sampled three times (December, February, May). Eventually, 75 samples were obtained for use as the test set for validation. Cloud-free bottom of the atmosphere Level-2A reflectance from 10 and 20 m resolution pixels was extracted at the sample locations using Google Earth Engine.

PLSR models were calibrated on the Sentinel-2 data derived from the ASD field data using leave-one-out cross validation (LOO) and then evaluated with the Sentinel-2 reflectance data downloaded from Google Earth Engine. For the Sentinel-2 models, pasture quality variables were $\log_{10}$ (CP, EDOM) or squared transformed (NDF, ADF). For the hyperspectral data, a waveband selection procedure was implemented (Kawamura *et al*. 2008). Starting from 168 bands at 10 nm, the waveband selection was performed by stepwise removal of the band with the lowest regression coefficient produced by the PLSR. The LOO was repeated at each step. $R^2$, Root Mean Squared Error (RMSE) and Ratio of Percent Deviation (RPD) were reported for each model. The RMSE of the Sentinel-2 models was back-transformed to facilitate the interpretation.

## Results and discussion

LOO of the Sentinel-2 model using the Sentinel 2 bands resampled from field spectroscopy produced $Rcv^2$= 0.60 for CP, $Rcv^2$=0.46 for NDF, $Rcv^2$=0.45 for ADF and $Rcv^2$=0.49 for EDOM. According to Viscarra *et al*. (2006) values of RPD between 1.4 and 1.8 indicate moderate predictive ability, which could allow qualitative assessments, while values over 1.8 indicate that quantitative assessments are possible. According to the test results of the Sentinel-2 models (Table 1), just qualitative assessments of CP would be possible. The rest of the variables showed poor predictive ability.

Table 1. Summary statistic of test results of predictions made with models fitted with ASD field data (173) to predict over Sentinel-2 imagery (75).

| Variable | n | Mean | nLV | R2 test | RMSE test | RPD test |
|---|---|---|---|---|---|---|
| CP % | 75 | 13.4 (20.7) | 3 | 0.54 | 3.32 | 1.55 |
| NDF % | 75 | 45.4 (37.9) | 3 | 0.46 | 6.58 | 1.38 |
| ADF % | 75 | 30.1 (22.2) | 3 | 0.28 | 4.55 | 1.26 |
| EDOM % | 75 | 62.8 (37.9) | 3 | 0.33 | 6.33 | 1.25 |

nLV- number of latent variables. Values in brackets represent the range of the variables.

The model calibrated with hyperspectral data resampled at 10 nm resolution showed promising results for CP (Table 2) which indicate good prediction ability and the possibility of quantitative assessments. Worse results were obtained for the rest of the variables for which only qualitative assessment might be possible in the case of NDF and EDOM.

Table 2. Summary statistic of LOO cross validation from models fitted with 10 nm resolution hyperspectral data using all bands (n=168) and with selected bands for each variable.

| | | | All bands (n=168) | | | | Selected bands | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | N | Mean | nLV | R2 cv | RMSE cv | RPDcv | nLV | R2 cv | RMSE cv | RPDcv | NB |
| CP % | 173 | 12.2 (24.0) | 11 | 0.79 | 2.48 | 2.17 | 12 | 0.83 | 2.19 | 2.46 | 19 |
| NDF % | 173 | 51.2 (46.5) | 11 | 0.60 | 6.35 | 1.59 | 6 | 0.66 | 5.89 | 1.71 | 36 |
| ADF % | 173 | 31.3 (29.1) | 3 | 0.40 | 4.74 | 1.30 | 6 | 0.46 | 4.49 | 1.37 | 7 |
| EDOM % | 173 | 59.0 (47.8) | 9 | 0.53 | 7.35 | 1.46 | 6 | 0.60 | 6.81 | 1.58 | 20 |

nLV- number of latent variables; NB: number of selected bands. Values in brackets represent the range.

The band selection procedure demonstrated that a high number of the hyperspectral bands are redundant (Kawamura *et al*., 2008). Similar and even better predictions can be obtained with fewer bands which could help to optimise the prediction of quality of grasslands using remote sensing. The main spectral regions selected were the red-edge (680-750 nm) and Near Infra-Red region (NIR) (800-1300 nm).

These results provide further insights into the possibilities of predicting forage quality of Mediterranean permanent grasslands using Sentinel-2 multispectral data and hyperspectral data provided by future satellites such as the Copernicus Hyperspectral Imaging Mission for the Environment (CHIME) (Nieke and Rast, 2018).

## Conclusions

Qualitative assessment of CP could be performed using Sentinel-2 images in permanent grasslands of open woodlands. Hyperspectral configuration might allow quantitative assessment of CP and qualitative of NDF with only 19 and 36 bands, respectively, from the red-edge and NIR regions mainly. Band selection showed that the number of bands used in hyperspectral data can be reduced maintaining or even improving the predictions.

## Acknowledgement

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# Remote sensing-based estimation of nitrogen fixation in organically managed legume-grass mixtures

Astor T., Grüner E. and Wachendorf M.

*Grassland Science and Renewable Plant Resources, Universität Kassel, D-37213 Kassel-Witzenhausen, Germany*

## Abstract

Organic farmers relying on legumes as the external nitrogen source need fast measurement techniques to determine the amount of fixed nitrogen ($N_{Fix}$) to enable numerous management decisions. Unmanned aerial vehicles (UAVs) are tools for a non-destructive assessment of grassland traits. The aim of this field study was to provide $N_{Fix}$ estimation models for two legume-grass mixtures through a whole vegetation period based on UAV multispectral information. Additionally, the annual $N_{Fix}$ was calculated. The treatments consisted of two legume-grass mixtures: clover-grass (CG) and lucerne-grass (LG), and pure stands of legumes and grass of both mixtures. From the multispectral data the reflectance and texture information, together with 13 spectral indices were used for modelling. A prediction accuracy of 82% was received when all vegetation and all spectral data were used. $N_{Fix}$ was overestimated at all cuts with the annual $N_{Fix}$ overestimated by 13.69 kg $ha^{-1}$ for CG and by 9.96 kg $ha^{-1}$ for LG. Annual $N_{Fix}$ prediction by multispectral information should be considered as a first approach for the support of farm management decisions, which still needs further improvement.

**Keywords:** texture analysis, grassland quality, nitrogen fixation

## Introduction

Legume-grass mixtures are important components of crop rotation systems, especially on organically managed farms in the temperate climate zone of Europe. Nitrogen-fixing legumes are essential for reducing the amount of external fertilizer needed for the following cash crop. The amount of fixed nitrogen ($N_{Fix}$) represents an important input variable at farm level needed for sustainable management decisions. Traditional methods for $N_{Fix}$ monitoring are based on destructive biomass sampling and are thus time and cost intensive. Non-destructive measurement techniques based on remote sensing can provide interesting approaches and improvements for field data acquisition of $N_{Fix}$ (Grüner *et al*., 2019). Legume-grass mixtures can be botanically, structurally and phenologically very diverse, as they, in contrast to other agricultural row crops, comprise different grasses legumes, and other herbs. This heterogeneity within the mixture cannot be measured by pure reflectance information alone. Texture features, derived from high spatial resolution images, proved to serve additional structural information, correlating well with grassland heterogeneity and are sensitive to the phenological growth stage of plants.

The aim of this study is to develop $N_{Fix}$ estimation models from UAV multispectral imaging of legume-grass mixtures with varying legume proportions (0-100%) and to evaluate the model prediction accuracy as a tool for the annual full season $N_{Fix}$ amount.

## Materials and methods

The data collection for this study was conducted in a field experiment in Neu-Eichenberg at an experimental farm of the Universität Kassel, in the year 2018. Field plots with a size of 1.50 m × 12 m were established and sown with a total seed rate of 35 kg $ha^{-1}$. The experimental treatments consisted of two legume-grass mixtures, clover-grass (CG) and lucerne-grass (LG), and additionally pure stands of the legumes and grass of both mixtures. Further information about the specific species composition in given by Grüner *et al.* (2019). These six treatments were sown in four randomized replicates, resulting in 24 plots in total. Biomass samples were collected at three harvest dates (17 May 2018, 20 June 2018, and 3 August 2018). Harvest dates were selected according to usual farming practice. The N concentration in the biomass was assessed by an elemental microanalyzer (Elementar vario MAX CHN, Langenselbold, Germany) and N content in the aboveground biomass was determined by multiplication of N concentration and dry matter biomass. $N_{Fix}$ was estimated by subtracting the N content from the

non-fixing pure stand of grass from the N content of the mixtures and the pure stand of legumes (i.e. difference method by Stülpnagel, 1982).

UAV flight missions were conducted before each harvest in the morning at a nearly equal sun position. A quadrocopter (DJI Phantom 3 Advanced, Shenzhen, China) was used equipped with a multispectral sensor (Parrot Sequoia, MicaSense Inc, Seattle, USA). The sensor captured the reflected light in four separate bands: green (530-570 nm), red (640-680 nm), red edge (730-740 nm) and near-infrared (NIR; 770-810 nm). Eight ground-control points (GCPs) were evenly distributed in the experimental layout and were georeferenced with a mean horizontal and vertical error of 0.02 m. Besides the average reflectance information of the four band, thirteen spectral vegetation indices and eight texture parameters for each spectral band (Haralick *et al*., 1973) were extracted for each plot and each harvest date. In total 49 variables were used as independent variables for modelling $N_{Fix.}$ The machine learning method partial least square regression was used for model calibration. In order to evaluate the additional values of texture features for the prediction, a model with and without texture features was calculated. A stratified cross-validation approach was applied, in which the whole dataset was repeatedly split into a calibration and validation dataset. To avoid bias by dividing the dataset, the cross-validation was run 100 times. All models were developed for both legume-grass mixtures combined (i.e. whole data) and for each mixture alone (i.e. clover-grass, lucerne-grass). To calculate the accumulated total $N_{Fix}$, the predicted and measured $N_{Fix}$ values for all legume-grass mixture plots were averaged for each harvest date. Summing the values for each harvest up, delivers information about the total annually accumulated $N_{Fix}$.

## Results and discussion

The modelling results for $N_{Fix}$ showed no consistent improvement by the integration of texture features. For the whole dataset and the clover-grass dataset the relative prediction error was slightly lower for the model without texture information (19% and 24% respectively) than for the models with texture information (20% and 37% respectively) (Table 1).

Table 1: Model summary for predicting $N_{Fix}$ with and without texture features using a partial least square regression. The prediction error ($rRMSEP_{Val}$) and the coefficient of variation ($R^2_{val}$) are based on 100 times 10 fold-cross-validation.

| | **Whole dataset** | | | **Clover-grass** | | | **Lucerne-grass** | | |
|---|---|---|---|---|---|---|---|---|---|
| **Texture (T)** | n | $R^2_{val}$ | $rRMSEP_{val}$ | n | $R^2_{val}$ | $rRMSEP_{val}$ | n | $R^2_{val}$ | $rRMSEP_{val}$ |
| **Without (T)** | 48 | 0.72 | 18.9 | 24 | 0.69 | 24.5 | 24 | 0.81 | 22.3 |
| **With (T)** | 48 | 0.70 | 19.6 | 24 | 0.49 | 36.9 | 24 | 0.83 | 20.9 |

In contrast, for the lucerne-grass dataset the model including texture information performed slightly better than the model without texture information (21% and 22%) (Table 1). The best model for $N_{Fix}$ was obtained for the whole dataset, which produced rather crop-unspecific models. However, our model validation strategy was limited due to the low number of samples and independent test dataset would be desirable for a more reliable assessment of prediction accuracy. Subsequently, our models were created based on datasets from one experimental site and one sampling year, which may limit the transfer of our modelling results to other locations and time periods.

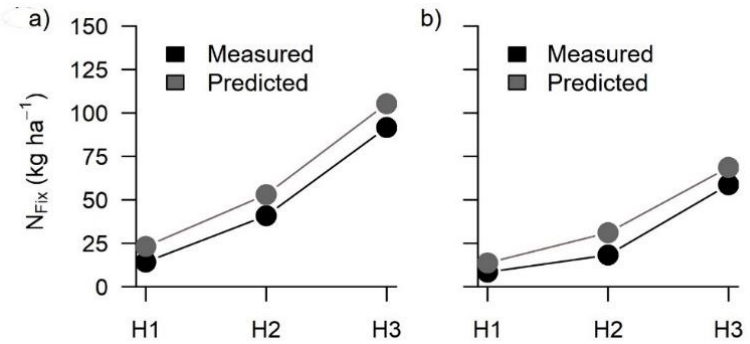


Figure 1. Accumulated total $N_{Fix}$ amount for a) the clover-grass mixture and b) lucerne-grass mixture based on field data (black) and predicted values (grey).

For practical farming information about the total annually accumulated N, $N_{Fix}$ is of relevance. The two legume-grass mixtures were of different biomass and $N_{Fix}$ levels, but showed very similar patterns concerning the trend of observed and predicted values (Figure 1). $N_{Fix}$ was overestimated at all cuts by 13.69 kg $ha^{-1}$ for CG and by 9.96 kg $ha^{-1}$ for LG.

This overestimation of $N_{Fix}$ for both legume-grass mixtures might be caused by the overall low total annual $N_{Fix}$ amount at our study site. This fact in combination with the small sampling size may have created difficulties in the modelling process.

## Conclusions

Non-destructive and fast $N_{Fix}$ prediction tools are desirable for practical farm management. We successfully developed a procedure for $N_{Fix}$ prediction for lucerne-grass mixtures by including texture features from a grey level co-occurrence matrix. Although prediction of $N_{Fix}$ seemed to be more complex than other traits like yield, strong relationships were found between $N_{Fix}$ and multispectral information under field conditions. However, the relationships must be interpreted with caution, as different impacts of N flux in the soil, air and plant affect N fixation of forage legumes in mixtures with grasses.

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# Monitoring rangeland biomass during wet and dry seasons from a video obtained with a simple digital camera

Diedhiou A.[1], Diatta O.[2], Ndiaye O.[2], Bossoukpe M.[1], Ngom D.[1], Julien L.[3,4], Toure I.[3,4], Diouf A. A.[5], Bayet T.[6], Cambier C.[6], Faye E.[7,8] and Taugourdeau S.[3,4]

*[1]Département Biologie Végétale, Faculté des Sciences et Techniques / UCAD, BP:5005 Dakar-Fann, Senegal; [2]Centre de Recherches Zootechniques de Dahra/ Institut Sénégalais de Recherches Agricoles (ISRA), BP 3120, Dakar, Sénégal; [3]CIRAD UMR SELMET,Montpellier, Senegal; [4]UMR SELMET, Univ Montpellier, CIRAD, INRA Institut Agro, 34000 Montpellier, France; [5]Centre de Suivi Ecologique, Rue Aimé Césaire x Léon Gontran Damas, BP 15532 Fann-Dakar, Senegal; [6]Sorbonne Universite, UCAD, IRD, UMI UMMISCO, F-75006 Paris, France; [7]UPR Hortsys, CIRAD-Univ Montpellier, Montpellier, 34000, France; [8]CIRAD, UPR Hortsys, Montpellier, 34000, France*

## Abstract

Photogrammetry is an image analysis that produces a 3D model of on object using a set of images taken from different positions. We tested this technique using a digital camera to produce a 3D model of 1m$^2$ of Sahelian rangeland grass. In 2019 we made measurements on 3 squares of 1m$^2$ (images capture and biomass measurement) in each of 10 days in the wet season and each month during the dry season. We analysed the images using PIX4D software. We extracted the volume and the colour indexes from the pix4D output. We used a random forest to predict the dry and fresh mass of the grass. The percentage of variance was 46.31% for the fresh mass and 40.46 % for the fresh mass. This tool could be used to monitor grass biomass during both wet and dry seasons and implemented in a grass observatory.

**Keywords:** structure from motion, Sahel, PIX4D, 3D model

## Introduction

Photogrammetry is a generic term that regroups all analyses where photography is used to make measurements. One of these analyses is called “Structure from motion.” (Frey *et al*., 2018). The concept of the analysis is that the structure (3D model) of an object is recreated from a set of images taken from different angles. The structure of motion is widely used on UAV images to create an orthomosaic and digital surface model of an ecosystem. Structure from motion can also be used from the ground with a digital camera. Previous work shows that 3D models obtained from digital cameras were linked with the mass of the herbaceous layer (Bossoukpe *et al.*, 2020). This work was carried out only at the end of the growing season (end of the wet season). The goal of the study reported here was to test the utilization of this approach to monitor the biomass during both the growing season and the dry season.

## Materials and methods

At the Dahra Research Station in northern Senegal, we made measurements on a natural rangeland in an enclosure during the wet season. The measurement started on 27 August 2019 (30 days after the first rain event of the 2019 wet season) and was made every 10$^{th}$ day until the end of the rainy season (here the 5 November). Measurements were made every month during the dry season to evaluate the quantity of straw material until 4 February 2020. For some videos the 3D model could not be made. 17 models were available for the wet season and 18 models for the dry season.

At each measurement, 3 squares of 1m x 1m of grass were sampled using a Camera Campark 20 with the camera in video mode. The video was taken horizontally at 1 m above the ground, oriented to the ground, taken along fives lines. We used video mode in preference to static images because it is easier to take one movie than taking 300 images of the squares. The video was in 1980*1080 resolution. We took between 350-400 images from this video.

The grass was cut and weighed to obtain the fresh mass, and samples were dried and weighed to obtain the dry mass. The video was analysed using the PiX4D software. The outputs of the PiX4D software were an orthomosaic and digital surface model. The project was scale with the square and a height

reference. We extracted the colour from the orthomosaic and height from the DSM. From the three colours we calculated several indices (Table 1).

Table 1. List of the Vegetation indices used (R: red, G: green and B: Blue).

| Acronym | Formula |
|---|---|
| NDGRI | (R-G)/(R+G) |
| NDBRI | (B-R)/(B+R) |
| NDBGI | (B-G)/(B+G) |
| Vari | (G-R)/(G+R-B) |
| Exg | G-0.39*R-0.61*B |
| GLI | (2*G-R-B)/(2*G+R+B) |

These indices were combined with the maximum and mean height obtained from the DSM. We used a random forest algorithm (package randomForest for R software) to predict the fresh and dry mass. Due to the unbalanced data of the masses, we used a square transformation and afterwards we analysed the residuals of the random forest between the different dates.

## Results and discussion

The random forest for the fresh mass explained 46.31% of its variability (44.41% for the dry mass). For both, the most important variable was the mean height obtained from the DSM; thus the NDGRI index (and the VARI indexes for fresh mass). This means that both colour and 3D variables can be used to evaluated the grass biomass. This results concord with work using UAV where both types of variable are important.

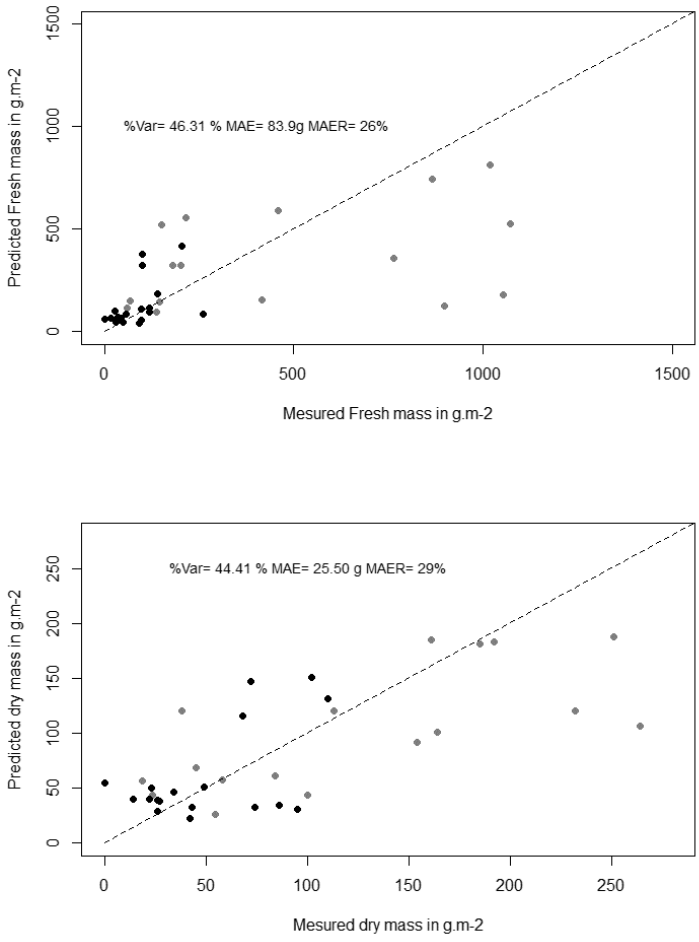


Figure 1. Predicted biomass obtained for the random forest versus measured biomass for the fresh mass and the dry mass. The black dots are the data in the dry season and the grey for the wet season, with the median absolute error (MAE) in g and the relative median absolute error (MAER) in %.

The residuals were different between the different dates of measurement. The random forest underestimates the mass at the end of the season but overestimates the mass at the beginning of the season. The same random forest model cannot therefore be used during the whole year. More data will be required to be able to build models for different times during the year.

## Conclusions

This work shows that some parts of the variability of the biomass of natural rangelands can be captured using a simple camera and the “structure of motion” process. This kind of process could be used to develop a participatory observatory of rangeland biomass growth based on a network of observers using cameras.

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# Detection of grassland mowing events with optical satellite time series data

Reinermann S.[1], Asam S.[2], Gessner U.[2], Schucknecht A.[3] and Kuenzer C.[1,2]

*[1]Department of Remote Sensing, Institute of Geography and Geology, University of Wuerzburg, 97074 Wuerzburg, Germany; [2]German Remote Sensing Data Center (DFD), Earth Observation Center (EOC), German Aerospace Center (DLR), 82234 Wessling, Germany; [3]Karlsruhe Institute of Technology (KIT), Institute of Meteorology and Climate Research – Atmospheric Environmental Research, Kreuzeckbahnstr. 19, 82467 Garmisch-Partenkirchen*

## Abstract

Grassland management – in particular the use intensity – determines its ecosystem services, like fodder production, carbon storage, freshwater generation and biodiversity. However, large-scale and spatially explicit information on grassland use intensity is often unknown. Here, an annual time series of high-resolution optical satellite data (Sentinel-2) for the year 2019 was used to detect mowing events in southern Germany. The pre-processed satellite time series was interpolated, smoothed and filtered and the daily Enhanced Vegetation Index (EVI) was calculated. Afterwards, mowing events were detected by applying an algorithm, which locates strong minima within the EVI time series per pixel. The results were validated by comparing them to mowing events extracted from daily pictures of grassland parcels on field scale. The number and dates of mowing events showed good results as 79% of the observed harvests were successfully detected. Mowing events were missed when the dense time series was disrupted by cloud conditions as the EVI response after mowing events usually lasted not longer than 14 days. Falsely detected mowing events were mostly related to grazing activities.

**Keywords:** grassland, mowing, use intensity, Sentinel-2, remote sensing, vegetation index

## Introduction

In Germany, grasslands are mainly agriculturally used for fodder production and are grazed and/or mown regularly. Furthermore, grasslands possess several ecosystem functions which play key roles concerning environmental impact and climate change, like carbon and nitrogen storage and cycling (Bengtsson *et al.,* 2019). The timing and frequency of grassland mowing strongly influences these functions. However, regional information on the mowing regime and therefore on yields and ecosystem services is mostly missing. Satellite data can be exploited in this regard as they are globally and frequently available at high spatial and temporal resolution (Reinermann *et al.,* 2020). In the past, optical satellite data have already showed promising results in detecting grassland management through time series analysis of the Normalized Difference Vegetation Index (NDVI) (Kolecka *et al.,* 2018; Griffiths *et al.,* 2020).

Here, we use optical data (Sentinel-2) to detect the mowing regime at regional scale and at high resolution (10 m) in southern Germany. The investigated grassland is heterogeneously used (from zero to six mowing events) and the algorithm is validated with an independent observation dataset.

## Materials and methods

In this study, Copernicus Mission Sentinel-2 data of the vegetation period (March to November) 2019 were analysed. The data consist of three spectral bands (bands 2, 4 and 8 with central wavelengths of 492.1 nm, 664.9 nm and 832.9 nm, respectively) at 10 m spatial resolution. The revisit time over southern Germany is 2 to 5 days. Data processing was conducted in Python (version 3.6). The Copernicus Grassland High Resolution Layer 2018 (EEA 2020) was used to extract the grassland areas in southern Germany. The Sentinel-2 time series was atmospherically corrected by applying the MAJA algorithm version 3.3 and clouds were masked out (Hagolle *et al.,* 2017). Based on the pre-processed data the Enhanced Vegetation Index (EVI) was calculated, which is sensitive towards vegetation greenness, structure and photosynthetic activity. In addition, EVI showed stronger reaction to grassland canopy change and less saturation effects than NDVI within the analysed data. The EVI time series were filtered, gap-filled and smoothed for each pixel: As the EVI at times showed values outside of a range of -1 to 1, only positive EVI values which were smaller than 2 were kept, assuming that other

values would not represent vegetated area. Large gaps (> 10 days) were filled linearly and a cubic splines interpolation was conducted on the EVI time series to generate daily information. These time series were smoothed using a Savitzky-Golay filter to reduce small fluctuations.

Following the developed mowing detection algorithm, local minima and maxima were detected for each pixel's time series. To check if the local minima in fact represents a mowing event, the difference between the EVI at the local minimum and at the previous local maximum was compared to an empirical threshold. The threshold which led to the best results when compared to real mowing events, was an EVI equivalent of 0.07. In addition, it was checked if the local minimum is followed by a local maximum with a difference of at least 0.02 EVI to guarantee that it is not a small minimum on a downward trend. If the criteria were fulfilled, the mowing event date was placed between the local maximum and local minimum.

In addition to the mowing events, the quality of the satellite information and the certainty of the mowing detection was assessed. Therefore, additional layers include the time interval and the gradient between local minima and maxima, and the data availability when a mowing event was detected. Furthermore, the number of valid scenes and the number and timing of large data gaps (more than 15 days) were investigated as additional quality information.

The mowing event detection is validated with an independent dataset consisting of daily wildlife camera and webcam images in southern Bavaria. The validation dataset includes information on a heterogeneous set of grasslands (49 in total) distributed among the study area. These grasslands are mown one to six times per year (more parcels two to four times than one, five or six times), resulting in 140 mowing events in total. This dataset was compared to the satellite-based event detection to calculate the accuracy of the algorithm.

## Results and discussion

Due to the dense Sentinel-2 time series and the strong reaction of the EVI to changes in the grassland canopy, mowing events could be successfully detected where cloud-free images were available. Even though the approach is pixel-based, the shapes of single grassland parcels are clearly visible when examining the mowing frequency map (Figure 1).

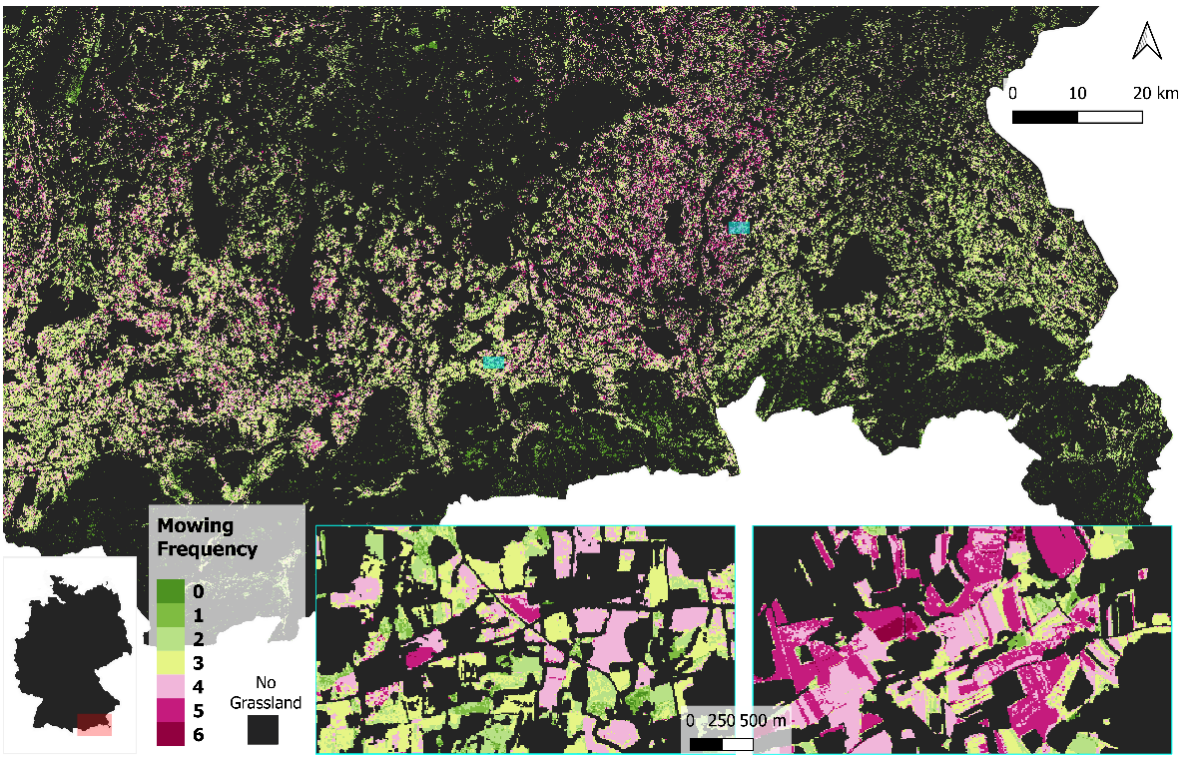


Figure 1. Grassland mowing frequency within the focus region in southern Germany. The images at the bottom are zooms. The country border information is from GADM (https://gadm.org/data.html).

In addition, the analysis of mowing events at this high resolution enables the perception of within parcel dynamics. The detected mowing frequency varies between zero and six events in 2019. Parcels with zero detected mowing events are probably grasslands, which are only grazed. The validation of the satellite-based mowing detection algorithm lead to good results (F1 score = 0.82; recall = 0.79; precision = 0.85). 79% of all mowing events of the validation dataset were correctly detected. The missed mowing events were almost always during cloudy conditions and therefore related to the unavailability of valid and dense data. The response within the EVI time series following a mowing event was only visible for about 15 days. 19 events were falsely detected as mowing events; these were mainly related to grazing activities on the parcels and were not biased towards a mowing frequency class.

This study shows that analyses based on optical satellite data are restricted to cloud-free conditions. To counteract resulting gaps within optical data time series, cloud-penetrating SAR data could be exploited to complement the mowing events detection.

## Conclusions

Grassland dynamics, such as the mowing regime, are clearly depictable from time series of vegetation indices based on optical sensors using a local minimum detection approach, given that cloud-free time series are available. Some grazing activities, but probably not all, were confused as mowing events by the algorithm.

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# Generalizability of multi- versus single-target regression for herbage mass and quality prediction from multispectral imagery

Simmler M.[1], Hart L.[1] and Liebisch F.[2]

*[1]Competitiveness and System Evaluation, Agroscope, Tänikon 1, CH-8356 Ettenhausen; [2]Agroecology and Environment, Agroscope, Reckenholzstrasse 191, CH-8046 Zürich, Switzerland*

## Abstract

Empirical models to estimate herbage mass and grass quality from multispectral imagery acquired by unmanned aerial vehicles (UAVs) often generalize poorly in relation to different types of grasslands. We therefore investigated whether the generalization performance can be improved by replacing the commonly used single-target regression algorithms by corresponding multi-target algorithm adaptations which can simultaneously predict herbage mass and grass quality (dry matter percentage, crude protein, and structural carbohydrates). By additionally considering the relationships between the target variables, these multi-target algorithm variants have the potential to yield better generalization performance. We found that for Partial Least Squares, K-Nearest Neighbours, and Random Forest, the multi-target variants tended to perform better than their single-target counterparts, while for Extremely Randomized Trees mostly the opposite was true. Given the usual lack of ground-truth data for the model to learn the underlying relationships, we suggest the use of multi-target regression be considered whenever several grass parameters are estimated.

**Keywords:** grassland, UAV, spectral reflectance, multi-target regression

## Introduction

Empirical models to estimate herbage mass and grass quality from multispectral imagery captured by unmanned aerial vehicles (UAVs) have great potential to support grazing and harvest scheduling. Such models have proved to perform particularly well when trained and applied on a single farm with grassland swards of one-to-few-plant species and low heterogeneity (e.g. Askari *et al.*, 2019). However, generalization to different, potentially more heterogeneous grasslands is not always applicable (e.g. Hart *et al.*, 2020). This poses a major challenge in model development for regions with spatiotemporally highly variable grasslands. In this study, we explored a new approach for developing herbage mass and grass quality models that, hypothetically, will improve the generalization performance. Instead of fitting separate models for herbage mass and different grass feed quality parameters, we integrated these questions using multi-target regression methods. These methods consider not only the relationships between the features (predictor variables), but also between the corresponding target variables, in our case herbage mass and grass quality parameters. Thus, it is presumed they describe better the underlying real world grassland situations and might better generalize as compared to corresponding single-target methods. To test this hypothesis, we conducted an *in-silico* experiment using a previously published dataset of UAV-acquired multispectral imagery and ground-truth data for herbage mass and several grass quality parameters, namely dry matter percentage and the concentrations of crude protein and structural carbohydrates (Hart *et al.* 2020). Employing a nested cross-validation (CV) strategy, we compare multi-target adaptations of Partial Least Squares, K-Nearest Neighbours, Random Forest, and Extremely Randomized Trees to their single-target variants.

## Materials and methods

*Dataset and feature extraction:* We used the dataset from Hart *et al.* (2020) which includes UAV-acquired multispectral data (green, red, red-edge, and near-infrared; ground sampling distance of ~5 cm) and ground-truth data for dry weight of the herbage mass per area (HM) and for several grass quality parameters, namely for dry matter percentage (%DM per fresh weight) and for the per-dry-weight concentrations of crude protein (CP) and of the structural carbohydrate fractions acid detergent fibre (ADF) and neutral detergent fibre (NDF). The dataset covers a very large diversity of grasslands ($n$ = 152): 18 multi-species grasslands located on six commercial farms in Switzerland monitored at different phenological growth stages (2 to 6 weeks) and seasons (spring to autumn).

Python 3.8 was employed for all data analyses. The features included the 21 spectral indices listed in Askari *et al.* (2019) and the four single spectral bands. These were extracted per-pixel and subsequently averaged for the 2.2 m x 5 m ground-truth plots omitting a 0.2 m wide margin to prevent boundary effects.

*Algorithm comparison:* We compared multi-target algorithm adaptations of Partial Least Squares (PLS), K-Nearest Neighbours (KNN), Random Forest (RF), and Extremely Randomized Trees (ExtraTrees) to their single-target variants. All algorithms were used as available in the Python package *scikit-learn* (v.0.23.2). In the multi-target case we used a single model to predict all five target variables (HM, %DM, CP, ADF, NDF). We employed a nested cross-validation (CV) strategy. The outer CV loop served exclusively the purpose of model validation while the inner CV loop is used for feature selection and hyperparameter tuning. The CV schemes were 5 times repeated 6-fold CV for the outer loop and (unrepeated) 5-fold CV for the inner loop. The performance and stability was determined as mean and standard deviation, respectively, of the coefficients of determination ($R^2$) over the 5x6 folds of the outer loop. Bayesian correlated t-test through the *two_on_single* function of the python package *baycomp* (v.1.0.2) was used to calculate the probability that the average performance ($R^2$) of the multi-target algorithm is higher than the performance of its single-target counterpart.

*Data scaling, feature selection, and hyperparameter (HP) tuning*: Target variables and features were *Yeo-Johnson*-transformed, scaled, and centred with the *PowerTransformer* (*scikit-learn*). The corresponding parameters defining the transformation/scaling were obtained for every cycle of the outer CV loop using only the training data. The $R^2$ was used as score for model selection (feature selection and HP tuning). For multi-target models the mean over the individual scores of the targets was used. Features were selected from the 4 spectral bands and the 21 spectral indices. For PLS and KNN, the feature selection procedure was combined with HP tuning as follows: for all combinations of HP values, a Sequential Forward Selection (SFS) based on cross-validation (inner CV loop) was conducted with the *SequentialFeatureSelector* from the Python package *mlxtend* (v.0.17.3). The tuned HPs with corresponding search ranges were *n_components* ∈ [1..31]) for PLS, and *n_neighbors* ∈ [2..10], *weights* ∈ {'uniform', 'distance'}, and *p* ∈ [1..4] for KNN. Additionally, for both PLS and KNN the number of features to select in SFS was tuned (*k_features* ∈ [*n_components*..25]). For RF and ExtraTrees, the feature selection and HP tuning was conducted in a computationally less demanding fashion, namely using *GridsearchCV* (*scikit-learn*) wrapped around Recursive Feature Elimination with *RFE (step = 0.5; scikit-learn*). For both RF and ExtraTrees, the HPs and search ranges were *max_features* ∈ (0.1, 0.2, …, 1), *min_samples_leaf* ∈ [1..10], and *max_samples* ∈ (0.2, 0.4, …, 1). Furthermore, *n_estimators* was set to 200 and for RF we tuned the HP *bootstrap* ∈ {True, False}.

## Results and discussion

Independent of the algorithm used, the generalization performance was poor (Figure 1; $R^2$ < 0.4 with few exceptions). Consistent across all models, %DM was the parameter that was best predicted ($R^2$ of 0.30–0.47). RF and ExtraTrees outperformed the simpler KNN and PLS. As indicated by the high standard deviation in $R^2$, the stability in generalization performance was very poor. Due to the low number and bandwidth of spectral bands, we suspect a lack of sensitivity to the plant properties. The instability in generalization performance furthermore suggests a limitation by the dataset being small considering the large diversity of grasslands it contains. Because of insufficient representation of this diversity in the dataset, the model presumably cannot adequately learn the relationships and thus is sensitive to the train-test split of the data. Particularly in this situation, using multi-target regression is a promising endeavour, as we can additionally exploit information that is already available without the need to collect more samples. However, in our experiment the multi-target models did not consistently outperform their single-target counterparts. For PLS, KNN, and RF, Bayesian correlated t-test indicated that the average generalization performance is more probable to be improved rather than diminished when using multi-target regression (with exception of %DM for RF). However, high probabilities (> 80%) for this improvement were only observed for the largest shifts in mean $R^2$ (0.05–0.1) corresponding to CP, ADF, and NDF when employing RF. Contrarily, for ExtraTrees the multi-target model performed worse in prediction of all targets but ADF, particularly pronounced for %DM where the mean $R^2$ dropped by 0.06.

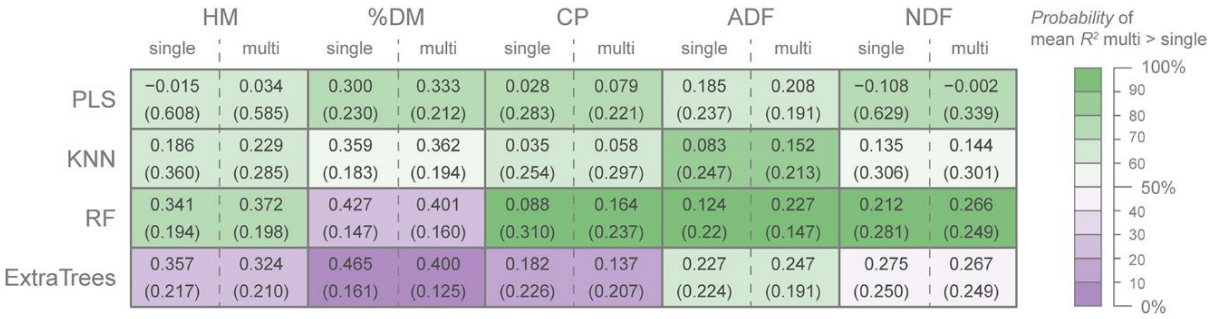


Figure 1. Mean cross-validation $R^2$ with standard deviation in parenthesis. The colours show the probability that the mean performance of the multi-target model exceeds the one of the single-target counterpart (Bayesian correlated t-test). Please note: the probability of the multi-target model's mean performance being worse is the complementary probability.

## Conclusions

The generalization performance of multispectral herbage mass and grass quality models improved in some, but not in all, cases when switching to multi-target algorithms. We suggest to investigate traits such as leaf area index or grass height as potentially beneficial co-targets and under which circumstances informative relationships between targets might weaken, e.g., at the end of the vegetative phase when herbage mass plateaued but grass quality declines.

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# From the field to the region – monitoring pre-Alpine grassland characteristics at different spatial scales

Schucknecht A.[1], Seo B.[1], Reinermann S.[2,3], Krämer A.[4], Asam S.[3], Atzberger C.[5] and Kiese R.[1]

*[1]Karlsruhe Institute of Technology (KIT), Institute of Meteorology and Climate Research – Atmospheric Environmental Research, Kreuzeckbahnstr. 19, D-82467 Garmisch-Partenkirchen; [2]University of Würzburg, Chair of Remote Sensing, Oswald-Külpe-Weg 86, D-97074 Würzburg; [3]German Aerospace Center (DLR), Earth Observation Center, German Remote Sensing Data Center, Oberpfaffenhofen, D-82234 Wessling; [4]WWL Umweltplanung und Geoinformatik GbR, Mozartweg 8, D-79189 Bad Krozingen; [5]University of Natural Resources and Life Sciences (BOKU), Institute of Geomatics, Peter-Jordan-Straße 82, A-1190 Vienna*

## Abstract

Grasslands in their various forms of appearance characterize the pre-Alpine landscape. Despite the economic value and significant role of plants in grassland carbon and nitrogen cycling, spatially explicit information on grassland biomass are rarely available. This study aims to develop routines to monitor grassland traits at different spatial scales. Field sampling campaigns were conducted in April 2018 and at multiple times during the growing seasons of 2019 and 2020 to collect in-situ data of aboveground dry matter biomass (DM) from differently managed grasslands. The campaigns were partially accompanied by unmanned aircraft system (UAS) flights to acquire very high resolution multispectral imagery at the field-scale. These data were complemented by time series of Sentinel-2 (S2) imagery to address the regional scale. In a first step, we tested different statistical modelling approaches and UAS input datasets to estimate DM for the single-date acquisition in 2018. Promising results were obtained by the machine learning algorithms random forest and gradient boosting machines (cross-validated $R^2$ of best model = 0.71). A first multi-temporal DM model for S2 imagery was developed and used to create regional maps. In the next phase we will adapt the algorithms to multi-temporal UAS data and compare the results across different scales.

**Keywords:** biomass, temperate grasslands, machine learning, UAS, satellite

## Introduction

Knowledge about available biomass and fodder quality is critical for grassland and livestock management. However, regularly updated spatially explicit information on grassland biomass and quality is rarely available. Remote sensing data offer the possibility to close this gap. Recent studies showed the potential to use UAS (e.g., Grüner *et al*., 2020; Wijesingha *et al*., 2020) and satellite data (e.g. Schwieder *et al*., 2020) for applications in temperate grasslands. The objective of our study was to develop and apply remote sensing-based models to estimate DM in pre-Alpine multi-species grasslands at the field and regional scale.

## Materials and methods

The wider Ammer catchment in southern Bavaria, Germany was selected as the study area. In-situ field and multispectral UAS data (4 bands; Parrot Sequoia [SEQ], Parrot Drones SAS, France) were acquired at selected sites and completed by Sentinel-2 (S2) imagery. A first pilot study with field sampling (10 plots of 30 m x 30 m, sampled at 12 subplots of 0.25 m x 0.25 m) and UAS flights was conducted in April 2018 (Schucknecht *et al*., 2020). Based on the experience from this study, the sampling design for the subsequent multi-temporal study was adapted. In 2019-2020 we sampled 11 plots (20 m x 20 m, each with 4 subplots of 0.5 m x 0.5 m) on differently managed grasslands at several times during the growing season to acquire information about bulk canopy height (CH, measured with a plate meter) and DM. The plots were sampled at different development stages at 2-8 dates per year (depending on logistical constraints). For the regional modelling, the subplot data of 2019-2020 was averaged per plot and sample date and related to the closest S2 pixel.

**Field-scale modelling.** For the 2018 study, we extracted the spectral data of the multispectral SEQ image at each subplot using a 3 x 3 pixel window and related it to the measured field data in a statistical modelling approach (7 plots; 84 observations for model development). We tested two machine learning

(ML) approaches: random forest (RF; Breiman, 2001) and Gradient Boosting Machines (GBM; Friedman, 2001) with different permutations of input datasets (raw reflectance values, vegetation indices [VI, n = 19], CH) to estimate DM. The CH was used in addition to spectral data to investigate the potential of canopy surface models derived from high-resolution UAS data as further predictor variable (e.g., Lussem *et al*., 2019). A 6-fold cross-validation and hyper-parameter calibration was applied to optimize the predictive models. Data from the 3 remaining plots were used for external model validation.

**Regional modelling.** We used S2 level 2A data from Mar-Nov 2019 and all available plot-level field data from 2019 (11 plots with varying number of sampling dates; in total 70 observations) to create a statistical model for DM estimation. S2 data was pre-processed with the MAJA algorithm version 3.3 and cloud mask (Hagolle *et al*. 2017), resampled to 20 m x 20 m pixel size, and the Enhanced Vegetation Index (EVI; Huete *et al*. 2002) was calculated. For each field observation the S2 reflectance data of 10 bands (excluding the atmospheric bands 1, 9, 10) and the corresponding EVI were extracted. If there was no cloud-free satellite observation from the day of field sampling, the days before (up to 4) were checked one by one, and then up to 4 days after to find the closest satellite observation. A RF model was built using all reflectance bands and the EVI as predictor variables. The data set was split into training (80%) and test data (20%). The developed model was used to model the DM in the Ammer region exemplarily for the 17/05/2019, a date on which UAS flights were also conducted to allow for later comparison between field and regional modelling approaches.

## Results and discussion

**Field-scale modelling.** The ML algorithms RF and GBM show very similar results for the estimation of DM in terms of coefficient of determination ($R^2$) and root mean square error (RMSE; Table 1). Both the addition of VI as well as CH improved the model performance compared to the sole use of raw reflectance values. As expected, the improvement for CH was stronger, as CH is a predictor from a completely different domain. The best model performance was achieved by a RF model utilizing all available input data. Our results indicate the benefit of additional predictors in the estimation of DM. However, for optimal prediction quality the acquisition of a digital canopy height model is necessary, requiring an additional UAS-based high-resolution RGB dataset.

Table 1. Cross-validated modelling results for DM estimation in 2018 with RF & GBM models using UAS data.

| Predictor set | $R^2$ (RF) | RMSE [g $m^{-2}$] (RF) | $R^2$ (GBM) | RMSE [g $m^{-2}$] (GBM) |
|---|---|---|---|---|
| Raw reflectance | 0.48 | 57.6 | 0.51 | 56.2 |
| Raw reflectance + CH | 0.69 | 44.2 | 0.70 | 44.1 |
| Raw reflectance + VI | 0.55 | 53.9 | 0.56 | 53.2 |
| Raw reflectance + CH + VI | 0.71 | 43.4 | 0.70 | 43.6 |

**Regional modelling.** The developed RF model using the regional data set achieved good prediction results for the multi-temporal DM estimation in 2019 ($R^2$ = 0.78, RMSE = 32.6 g $m^{-2}$). The calibrated model was subsequently used to estimate DM in the Ammer region (Figure 1). This satellite-based approach relies solely on multispectral information from S2 as input data and the field data base to build the model. The modelling of the temporal evolution of the grassland DM in 2019 in the Ammer region is underway. Here, the availability of cloud-free S2 images is the most crucial element.

## Conclusions

ML algorithms that utilize multispectral remote sensing data showed promising results for the estimation of DM in pre-Alpine grasslands at field and regional scales. The choice of input feature was more important than the one of the ML model. Both, the UAS and the satellite approach rely on a sound field data sets for calibration and validation.

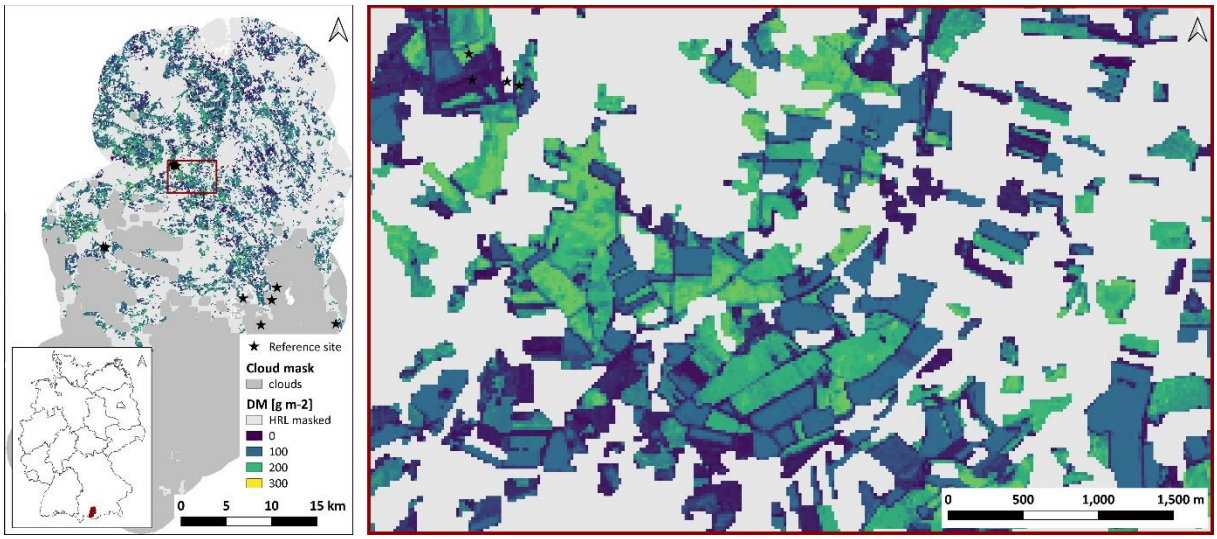


Figure 1. Estimated DM (linear colour interpolation) on 17/05/2019 based on S2 data in the Ammer region (left) and a zoom-in (right). Reference sites partially covered by clouds (grey); study area masked with High Resolu-tion Grassland Layer 2015 (light grey, © European Union, Copernicus Land Monitoring Service 2018, EEA)

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# UAV to measure canopy height and plot biomass in a lucerne variety trial

Surault F., Roy E., Mahieu S., Combes D., Ghesquière M. and Julier B.

*INRAE, UR P3F, CS 80006, 86600, Lusignan, France*

## Abstract

The objective was to test the reliability of height and biomass measurements of lucerne by digital photogrammetry using an unmanned aerial vehicle (UAV). Height measurements were recorded on a variety trial involving 440 microplots of pure stand lucerne over two years from April 2019 to November 2020. For comparison, manual measurements of plant height and dry matter yield (DMY) were performed the same day as the UAV acquisitions at the end of eight growth cycles. The model Phantom 4 Advanced (DJI) with mounted RGB camera equipped with a 20-megapixel CMOS sensor was used for image acquisition. The flights occurred at an altitude of 9 m to achieve a resolution of 2 mm. When UAV heights were calculated using 100% of the pixels of the canopy height model, the correlation between heights and DMY derived from UAV acquisitions were greater than those derived from manual measurements. Regressions on the set of flights per year between UAV heights and DMY were similar with high correlation coefficients in 2019 and 2020 (0.89 and 0.96, respectively). We conclude that UAV equipped with a high-resolution RGB camera allow rapid acquisition and data treatment and predicting reliable results of canopy height and DMY for the lucerne.

**Keywords:** photogrammetry, dry matter yield, phenotyping, RGB imagery, remote sensing, forage species

## Introduction

With more than 33 million hectares sown worldwide, lucerne (*Medicago sativa* L.) is the most cultivated perennial forage legume. Due to its high nutritive value, including 15 to 22% crude protein, this legume is well-suited for animal feed and its cultivation provides many ecological and environmental benefits such as improving soil fertility and preventing soil erosion. However, improvement in lucerne biomass is in high demand. Genetic progress for this complex trait has lagged behind other crops due to the tedious measurements required by the phenotypic selection work. Because of the perennial nature of this species, measurements of plant dry matter have to be repeated 4 to 5 times per year for two years while height has to be measured several times per growth cycle. Moreover, biomass is a complex trait controlled by a combination of multiple genes and their interactions with environmental factors so that breeding programmes should be implemented across multiple environments. To achieve rapid genetic improvement, high selection intensity with fast and low cost phenotyping tools is required. Sensors mounted on unmanned aerial vehicles (UAVs) are versatile and affordable tools allowing flights to be performed on large collections of breeding varieties with a high temporal resolution to follow the crop status and the dynamic of crop growth (Borra-Serrano *et al.*, 2019; Surault *et al.*, 2019). Images deliver a high spatial resolution. The main limitations remain in the fine-tuning required for each crop and trait (Hund *et al.*, 2019). Recently, Tang *et al.* (2021) developed a model incorporating four features resulting from simultaneous UAV RGB and multispectral acquisitions that was able to predict 50 to 70% ($R^2$) of biomass variation. The objective was to test the reliability of height and biomass measurements of plant canopy on a variety trial of lucerne by digital photogrammetry using UAV RGB only.

## Materials and methods

Height measurements were carried out on a variety trial comprising 440 microplots of pure stand lucerne at the end of 8 growth cycles from April 2019 to November 2020. The trial was organized in a 4 block augmented design. A total of 387 varieties were tested including 5 varieties with 6 replicates (n = 6), 28 varieties with 2 replicates (n = 2) and 354 with 1 replicate (n = 1). The surface of each plot was 5 m². The model Phantom 4 Advanced (DJI) with mounted RGB camera equipped with a 1 inch and 20-megapixel CMOS sensor oriented in a nadir position was used for image acquisition. The flights occurred at an altitude of 9 m with 2 m spacing between the flying lines to achieve a ground soil distance of 2 mm and ensuring an overlap of 80% between images. Plant heights, measured manually using a ruler or a rising plate meter (RPM) and UAV acquisitions were performed at the end of each growth cycle just before mowing with a Haldrup plot harvester. Plant dry matter yields (DMY) were assessed

from the fresh biomass collected at the time of the mowing and the dry matter proportion in samples. The SfM software Agisoft Photoscan v1.2.6 Professional Edition (Agisoft LLC) was used to build georeferenced orthophotos and the digital elevation models (DEMs) with a resolution of 4 mm. The DEMs resulting from each measurement date were linked to each other using 60 ground control points. Canopy height models (CHMs) were built from the DEMs under QGIS v2.14.16Essen (QGIS Geographic Information System; Open Source Geospatial Foundation Project). For each plot, the CHMs were obtained by subtracting altitude of the pixels of the DEM at the date of measurement to the altitude of the pixels of the DEM after a mowing. From a previous test, 100% of the pixels of the CHM were used for the estimation of UAV heights. The correlation of measured and UAV plant heights with observed dry matter yield was evaluated.

## Results and discussion

Correlations were established per growth cycle between manual and UAV heights with DMY (Figure 1A and B).

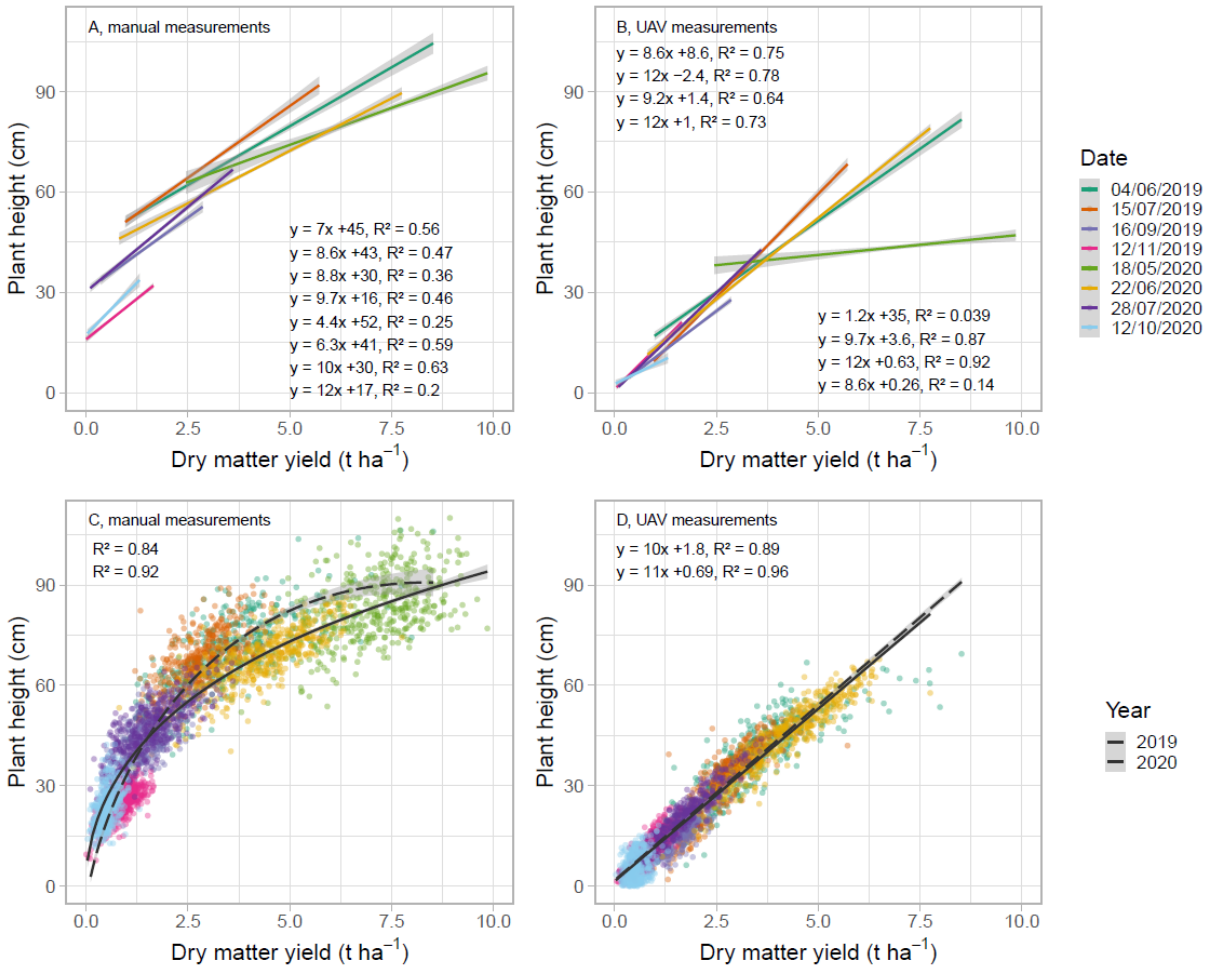


Figure 1. Comparison of manual and UAV height measurements for the prediction of the observed dry matter yield of lucerne. Regression are presented per date (A, B) and per year (C, D). Confidence intervals are displayed in grey around the regression lines.

Higher correlation coefficients were obtained between UAV heights and DMY (0.75, 0.78, 0.64, 0.73, 0.039, 0.87, 0.92, 0.14) than between manual heights and DMY (0.56, 0.47, 0.36, 0.46, 0.25, 0.59, 0.63, 0.2) except for two dates. Due to lodging occurrence on most of the microplots, the flight of the 18/05/2020 ($R^2$ = 0.039, Figure 1B) had to be discarded from the correlations. In this situation, height performed manually with a ruler on extended plants predicted more correctly DMY than UAV height. Regressions obtained per cycle (Figure 1B) and on the set of flights per year (Figure 1D) between UAV heights and DMY were similar with high correlation coefficients in 2019 and 2020 (0.89 and 0.96,

respectively). The correlation coefficient of the complete set of flights was 0.94 (data not shown). Correlations between plant heights derived from manual measurements with a ruler or a RPM and DMY (Figure 1C) were less reproducible than those derived from UAV measurements (Figure 1D).

## Conclusions

We conclude that using UAV equipped with a high resolution RGB camera allows a reliable prediction of and lucerne dry matter yield ($R^2$ = 0.94). Widespread use of this new method should significantly contribute to fasten genetic progress in lucerne breeding.

## Acknowledgments

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# Using UAV-borne imagery for plant height measurements of perennial forage species by photogrammetry

Roy E., Mahieu S., Surault F., Combes D., Louarn G., Frak E. and Ghesquière M.

*INRAE, UR P3F, CS 80006, 86600, Lusignan, France*

## Abstract

The choice of the pixel resolution for the production of the digital elevation model (DEM) using Structure from Motion (SfM) software can largely influence the time of data treatment and the required data storage capacity. The objective of this study was to investigate the effect of the DEM resolution on height measurements of five perennial forage species. Images were acquired with a UAV, model Phantom 4 Advanced (DJI, China). Three flights were repeated 5 days apart in June 2018 on a trial involving pure stand microplots of two grass (orchard grass and tall fescue) and three legume species (alfalfa, red clover and white clover). The flights occurred at an altitude of 9 m above the ground to achieve an image resolution of 2 mm. The DEMs were built with a pixel resolution of 2, 4 and 8 mm using the SfM software Agisoft Photoscan (Agisoft Ltd, Russia). The results were compared to the height measured manually with a ruler at the same time as UAV acquisitions. The effect of DEM resolution on height measurements differed according to the species. For the three legume species, similar and reliable regressions between manual and UAV height measurements were obtained with the three tested resolutions for the three dates ($0.88 < R^2 < 0.97$). The most reliable regressions were obtained for the orchardgrass ($R^2 > 0.81$) with a DEM resolution of 4 mm. The results obtained for tall fescue were less reliable than for the other species. The highest regressions between manual and UAV height measurements for this species ($0.56 < R^2 < 0.71$) were obtained with the lowest DEM resolution (8 mm).

**Keywords:** photogrammetry, plant height, phenotyping, RGB imagery, remote sensing, forage species

## Introduction

Phenotyping methods were identified as the main limiting factor to the improvement of annual yield gain of cultivated grassland and their resilience to biotic and abiotic stresses (Gebremedhin *et al.*, 2018). One way to overcome the slow progress in genetic improvement in forage species is through the improvement of precision phenotyping tools. Unmanned aerial vehicles (UAV) equipped with high resolution consumer grade Red-Green-Blue (RGB) cameras are versatile and affordable tools that allow the screening of large collections of breeding varieties in a high-throughput manner (Borra-Serrano *et al.*, 2019; Hund *et al.*, 2019; Surault *et al.*, 2019). However, the method is not yet widely used in routine in breeding programmes due to the particular precautions required for image acquisition with good quality and the complex data computation process that has to be fine-tuned for each trait and crop (Hund *et al.*, 2019). Images can be captured with sufficient quality only if different parameters are considered when planning a flight. Such parameters are the number and placement of ground control points (GCPs) for georeferencing, the flying height and the sensor size and resolution that determine the range of ground covered by a sensor pixel (GSD). Overlapping higher than 60% between images also needs to be achieved. Images are processed using a Structure from Motion (SfM) software to generate highly detailed orthophotos and digital elevation models (DEMs) that deliver a millimetre pixel resolution. The choice of pixel resolution to build the DEMs influences the time of data processing and the disk space required for data storage, which can be problematic when data for many breeding programmes have to be analysed. This pixel resolution can be modified at the time of the DEMs building while its effect on the canopy height measurements is not known. The objective of this study was to investigate the effect of the DEM resolution on canopy height measurements of five perennial forage species.

## Materials and methods

Data were acquired during the second year of a trial organized in 4 blocks and involving 140 pure stand microplots (6.25 m²) of two grasses: orchardgrass (*Dactylis glomerata* L.) and tall fescue (*Festuca arundinacea* L.) and three legume species: alfalfa (*Medicago sativa* L.), red clover (*Trifolium pratense* L.) and white clover (*Trifolium repens* L.). The species were sown at a single or double density. Half of the microplots sown with grasses were fertilized with nitrogen at 50 kg N $ha^{-1}$. Plant heights were

measured on three different days in June 2018. Manual height was performed using a ruler and the resulting values used as the average of three measurements recorded per plot. On the same days, three flights were repeated using the model Phantom 4 Advanced (DJI, China) with mounted RGB camera equipped with a 1 inch and 20-megapixel. The CMOS sensor oriented in a nadir position was used for image acquisition. The flights occurred at an altitude of 9 m above ground with 2 m spacing between the flying lines to achieve a GSD of 2 mm and ensuring an overlap of 80% between images. Twenty GCP equally spread in the four blocks were georeferenced. The SfM software Agisoft Photoscan v1.2.6 Professional Edition (Agisoft LLC, Russia) was used to build georeferenced orthophotos and the DEMs with a pixel resolution of 2, 4, and 8 mm. The DEMs resulting from each measurement date were linked to each other using the 20 GCPs. Canopy height models (CHM) were built from the DEMs under QGIS v2.14.16Essen (QGIS.org, 2021). For each plot, the CHM were obtained by subtracting altitude of the pixels of the DEM at the date of measurement to the altitude of the pixels of the DEM after a mowing. The correlation coefficients of the regression between manual and UAV plant height measurements obtained from the different resolution of the DEMs were compared.

## Results and discussion

The average variance value after adjustment of the GCPs was 2.9 cm, 2.5 cm and 1.4 cm on X, Y and Z coordinates, respectively. The time of data processing, and the disk space required for data storage, were divided by 12.3 and 14.6 respectively when the DEM resolution reduced from 2 mm to 8 mm. The average percentage of null pixels of the DEMs increased from 0.9 to 8.2% with increasing resolution from 8 mm to 2 mm. The pixel distribution between the horizontal layers of the CHM was also modified by the DEM resolution for all species (data not shown). The effect of the resolution on height measurements differed according to the species. The value of the highest pixel of the CHM was, on average, increased from 7.2 to 14.1 cm according to the species when increasing pixel resolution of the DEMs from 8 mm to 2 mm. In legumes, similar and reliable UAV heights were obtained with the three tested resolutions and have not been further detailed across species (Table 1).

Table 1. Effect of the DEMs resolution 2, 4 and 8 mm on the coefficients of the regressions between UAV (y axis) and manual (x axis) height measurements, three dates in June 2018.

| DEM Resolution | $R^2$ | | | Slope | | | Intercept | | |
|---|---|---|---|---|---|---|---|---|---|
| | 14/06 | 19/06 | 25/06 | 14/06 | 19/06 | 25/06 | 14/06 | 19/06 | 25/06 |
| **Tall fescue** | | | | | | | | | |
| 2 mm | 0.39 | 0.40 | 0.41 | 1.01 | 1.11 | 0.97 | -7.75 | -3.92 | 0.26 |
| 4 mm | 0.50 | 0.50 | 0.48 | 1.11 | 1.30 | 1.07 | -12.99 | -10.79 | -5.21 |
| 8 mm | 0.64 | 0.56 | 0.71 | 1.05 | 1.42 | 1.32 | -14.12 | -16.02 | -15.86 |
| **Orchardgrass** | | | | | | | | | |
| 2 mm | 0.85 | 0.79 | 0.93 | 1.07 | 1.29 | 1.19 | -8.70 | -7.63 | -7.90 |
| 4 mm | 0.86 | 0.81 | 0.94 | 1.10 | 1.29 | 1.20 | -11.62 | -9.39 | -9.53 |
| 8 mm | 0.85 | 0.82 | 0.94 | 1.13 | 1.36 | 1.23 | -14.95 | -13.58 | -12.38 |
| **Legumes** | | | | | | | | | |
| 2 mm | 0.97 | 0.88 | 0.96 | 1.07 | 0.98 | 0.95 | -4.34 | 2.70 | 4.89 |
| 4 mm | 0.96 | 0.89 | 0.96 | 1.07 | 0.96 | 0.95 | -5.00 | 3.05 | 4.69 |
| 8 mm | 0.96 | 0.90 | 0.96 | 1.07 | 0.98 | 0.96 | -5.87 | 2.08 | 3.59 |

High correlation coefficients (0.88 – 0.97) were achieved between UAV and manual heights at the three resolutions (Table 1). For orchard grass, the DEM resolution had no effect on $R^2$ and modified only very slightly the slope; the gap on the intercept was reduced from 4.48 to 6.25 cm according to the date with increasing DEM resolution from 8 mm to 2 mm. The regression obtained between UAV and manual heights for tall fescue was less reliable than for the other species. For this species, the highest $R^2$ was obtained with the lowest DEM resolution (8 mm) for the three dates ($0.56 < R^2 < 0.71$) while the gap on the intercept was reduced from 6.37 to 15.6 cm according to the date at the highest resolution (2 mm) and that the slopes were decreasing closer to 1 (Table 1). The differences between species probably result from the difference in shape and width of plant leaves.

## Conclusions

Our results show that the pixel resolution used to build the DEMs had a significant effect on plant height measurement, varying according to plant species. For the three forage legume species, and also for orchardgrass, reliable canopy height estimations have been achieved in comparison to those for manual heights. A pixel resolution of 8 mm of the DEMs provides the best results for the three legume species, while this was obtained in orchardgrass at a resolution of 4 to 2 mm. The results obtained in tall fescue were not fully satisfactory. Further analyses are still required for this species.

## Acknowledgement

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# Estimating grassland biomass using multispectral UAV imagery, DTM and a random forest algorithm

Sutter M., Aebischer P. and Reidy B.

*School of Agricultural, Forest and Food Sciences HAFL, Bern University of Applied Sciences, Switzerland*

## Abstract

A prerequisite for efficient pasture management is the regular estimation of the dry matter yield (DMY) by means of a rising plate meter (RPM). With the latest generation of unmanned aerial vehicles (UAV) equipped with a real-time kinematic (RTK) positioning system and a multispectral camera, it should be possible to measure sward heights and to estimate dry matter yields. To investigate this possibility, we developed an algorithm enabling a digital terrain model to be calculated from the digital surface model of grassland. DMY is estimated using a random forest estimator. Initial estimates at a previously unseen site achieved a root-mean-square error (RMSE) of 332 kg DM $ha^{-1}$. The results demonstrate that UAVs enable DMY predictions with an accuracy level close to RPM measurements. The underlying algorithm will be further developed and adapted to a wider variety of pasture types and meadows.

**Keywords:** grassland, machine learning, random forest, NDVI, remote sensing, dry matter yield

## Introduction

In Switzerland, more than 70% of the utilised agricultural area consists of grasslands with a very diverse species composition and a heterogeneous growth pattern. A prerequisite for efficient grazing management is the regular estimation of the dry matter yield (DMY) by manual measurements of the sward height using a rising plate meter (RPM). With the latest generation of unmanned aerial vehicles (UAVs) equipped with a real-time kinematic (RTK) positioning system and a multispectral camera, it should be possible to measure sward heights and to estimate DMY over large areas with high accuracy (Viljanen *et al.,* 2018). However, to date, such approaches have required manual georeferencing with complex data processing. The calculation of a digital terrain model (DTM) based on a digital surface model (DSM) could help to overcome the limitations of manual georeferencing. This would make it possible to measure the vegetation height without prior marking of the area of interest with ground control points (GCPs) and subsequent referencing of the image, resulting in a significant improvement in the degree of automation. In this paper, we present an algorithm to calculate a DTM based on a DSM of pastures and meadows allowing DMY to be estimated based on a random forest model.

## Materials and methods

DMY was calculated using a random forest estimator. To provide the model with robust data and to make it as reliable as possible to reflect seasonal growth patterns, swards of intensively managed meadows (experimental plots with a size of 4 $m^2$, 45 plots x number of overflights: n = 1026) at two different locations were flown over weekly with a UAV (DJI P4 Multispectral) from April to October 2020. Data from two additional sites of pastures from commercial farms (where partial areas of 30 $m^2$ were evaluated, 38 plots x 4 overflights: n = 152) were used as training data. In total, the training data set thus comprised 1178 polygons from four different sites and two utilization types (grazing and mowing). After flying over the meadows with the UAV, the DMY was determined by cutting (cutting height: 5 - 7 cm), weighing and drying sward samples (target variable). The model was tested with test data (n = 106) not included in the training data set from independent sites.

The pictures were taken without ground control points and were stitched to a 3-D model with Agisoft (Agisoft Metashape, 2020). We used a calibrated reflectance panel (MicaSense) with a nominal reflectance of 0.6 to radiometrically correct reflectance. The gain settings captured from the sunlight sensor were not used for radiometric calibration. A pixel size of 4 cm was chosen for the 3D model (DSM) and a pixel size of 3 cm for the orthomosaic with the five channels blue, green, red, red edge and near-infrared.

Based on the DSM, a DTM was generated with a kind of 'digital mower' making ground control points obsolete. The missing data were first interpolated and then the minima in the DSM were searched through a minimum filter of 1.5 on 1.5 metres. The DTM was subsequently smoothed with a two-dimensional Gaussian filter of 4.5 on 4.5 metres. The difference between the DSM and the DTM resulted in the sward height per pixel. To counteract divergences in the DTM, especially in areas with more complex topographies, the calculated sward height per pixel was smoothed again. For flat meadows this step seems redundant and the re-smoothing hardly changed the distribution of the grass height. Finally, the calculated average sward height for each plot was used for further calculations (Figure 1).

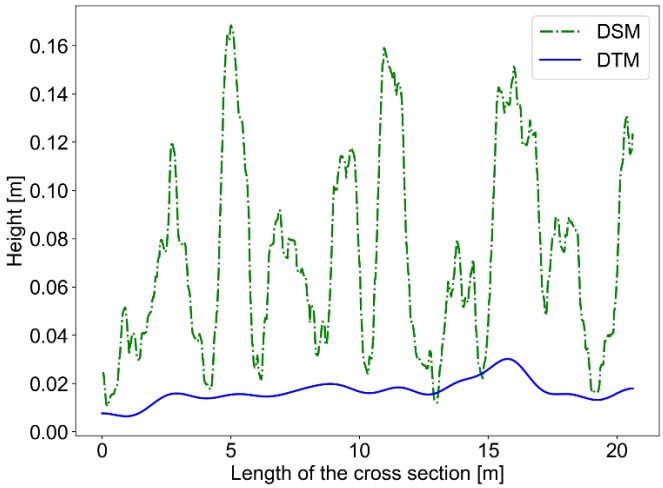


Figure 1. Example of a digital terrain model (DTM) calculated on the basis of an automatically generated digital surface model (DSM).

## Results and discussion

To evaluate the DTM, meadows at three different locations (Figure 2) were flown over before and immediately after cutting. The difference between the two flights represents the average height of the swards. The R-squared value of 0.9 indicates that the results of the digital mower were a good representation of the sward heights measured in the field.

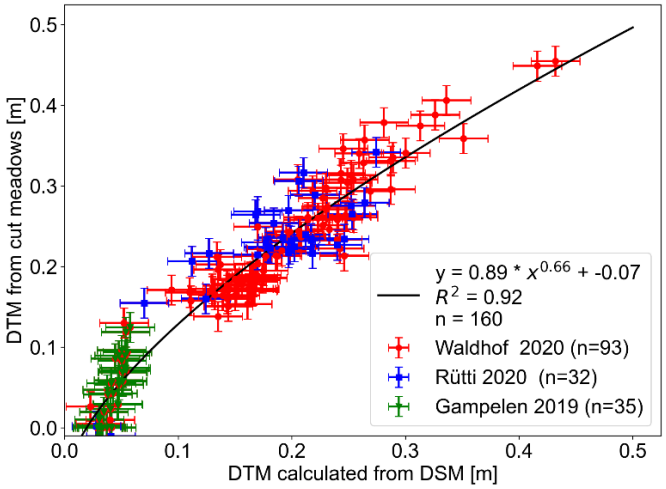


Figure 2. Evaluation of the 'digital mower' at three different locations in 2019 and 2020.

The DMY data was incorporated into the model as target variable. Based on the 3D model (DTM and DSM) and the images from the multispectral camera, 42 input variables were available for modelling the DMY.

The random forest model considers 14 input variables to estimate the target variable DMY: Average sward height, standard deviation of the average sward height, maximum and minimum sward height, normalized difference vegetation index (NDVI), green normalized difference vegetation index (GNDVI), soil-adjusted vegetation index (SAVI), green chlorophyll index (GCI), red chlorophyll index (RCI), normalized difference red edge (NDRE), excess green index (EGI), excess red index (ERI), months of data collection and shutter speed. In this model, average sward height (17%), SAVI (14%), NDVI (14%), GCI (13%) and month (9%) are the most important input variables. The high relevance of the average sward height in the model is explained by the saturation effect that occurs in the vegetation indices: above a certain biomass, the vegetation indices are no longer accurate representations. In our dataset, saturation becomes apparent from around 2500 kg DM $ha^{-1}$. As a consequence, the indices for a biomass of 2500 kg DM $ha^{-1}$ hardly differ from those for 4000 kg $ha^{-1}$ (i.e. NDVI 0.9 and 0.95, respectively). This limitation of the vegetation indices is already well described in the literature, for example by Prabhakara *et al.* (2015).

The test results of our model yielded a root-mean-square error (RMSE) of 332 kg DM $ha^{-1}$ and a residual standard error of 335 kg DM $ha^{-1}$. The mean error of -90.21 kg DM $ha^{-1}$ indicates that the model tends to underestimate ground truth. Schori (2020) tested RPM over several years at different sites in Switzerland. The author concluded that RPM estimates grass biomass well ($R^2 = 0.77$). However, despite these high R-squared values, the residual standard error was 272 kg DM $ha^{-1}$.

## Conclusions

Our results show that it is possible to estimate the DMY of pastures and meadows with a commercially available UAV, although the accuracy of the estimate with the available training data is slightly lower compared to that of a manual measurement with a RPM. To enable the digital mower to work, minima must be present within the area. However, with our intensively managed plots (cuts every four weeks, annual yield ≥12 Mg $ha^{-1}$), we were able to find enough minima to model the DTM at any given time. To further reduce the estimation error, training data will be supplemented with additional data from swards with greater botanical heterogeneity and extended to the DMY range < 1000 kg $ha^{-1}$ in the future.

## Acknowledgements

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# Remote sensing data fusion and feature selection for biomass prediction in extensive grasslands invaded by *Lupinus polyphyllus*

Schulze-Brüninghoff D., Astor T. and Wachendorf M.

*Grassland Science and Renewable Plant Resources, Universität Kassel, Germany*

## Abstract

Heterogenous, extensive grasslands are at risk from the spread of invasive plant species which can pose significant impacts from the ecosystem down to the species level. The aim of this study was to develop prediction models from sensor data fusion for fresh and dry matter yield (FMY/DMY) in extensively managed grasslands with variable degrees of invasion by *Lupinus polyphyllus*. Therefore, a terrestrial 3d laser scanner and a drone based hyperspectral camera was used. VSURF, a feature selection procedure was used to remove irrelevant features and ALE (Accumulated Local Effects) plots were utilized to gain a deeper quantitative understanding of a single feature on the prediction output. Models from hyperspectral data solitarily had the lowest prediction performance, followed by models derived from 3d laser data. A fusion of both sensor systems gained the highest prediction performance. Remote sensing data fusion from complementary sensor systems in combination with feature selection can increase the biomass prediction performance as well as the simplicity and interpretability of biomass prediction models. Further, the lowest over- and underprediction was found with lupine contributions between 20 and 40%. It could be shown that the abundance of invasive species can impact the quality of remote sensing-based FMY and DMY prediction in grasslands.

**Keywords:** sensor fusion, biomass prediction, feature selection

## Introduction

The biosphere reserve Rhön is a historically grown landscape, characterized by heterogenous grasslands which provide valuable ecosystem services and are a wildlife habitat for multiple endangered species. The spread of invasive species like *Lupinus polyphyllus* transforms the ecosystem and degrades the biocenosis quality for native species which were adopted to the original environment. Further, dominance of *L. polyphyllus* also changes the heterogeneity of the sites and this increases the difficulty of gaining its qualitative and quantitative parameters. As remote sensing methods allow to survey larger areas, and thereby to access information on biomass yield in large spatial dimensions, they provide potentially high value for heterogenous grassland sites, where traditional yield estimation methods would be highly time consuming. To improve the performance of remote sensing methods towards enhanced biomass models, sensor fusion is considered a good extension (Schulze-Brüninghoff *et al.*, 2020). Therefore, 3d point cloud information derived by a terrestrial laser scanner (TLS) and hyperspectral drone-based data was combined to predict biomass in four heterogenous extensive grasslands. To reduce redundancy of the sensory datasets and increase model performance and interpretability a feature selection was applied.

## Materials and methods

Data collection took place at four sites. A *Nardus stricta* grassland (NS), a *Trisetum flavescens* grassland (TF) and two sites invaded by *L. polyphyllus* (NSL, TFL). Each site had 15 plots and 3 cutting dates (15 June, 27 June and 11 July). At each cutting date drone-based hyperspectral data were collected with a Firefly S185 SE (Cubert GmbH, www.cubert-gmbh.com) at a spectral range from 450 to 998 nm (138 bands) and a spatial resolution of 50x50 pixels per image. Flight altitude was at 20 m above ground level with a pixel size of 20 cm and images were taken with 80% overlap for image stitching.

Afterwards, 3d data were collected with a terrestrial laser scanner (Leica Scan Station P30) with a spatial resolution of 3.1 mm (@ 10 m). To reduce shadow effects each plot was scanned from two opposite directions. Destructive ground reference samples were cut for each plot in three randomly selected subplots of 1 m² with a stubble height of 5 cm. Another 3d point cloud was collected in early spring of the same year to calculate a digital elevation model (DEM) for all sites. Fresh matter was weighed, and dry matter was measured after 48 h at 105° C.

Point cloud data were processed with R software (R Core Team 2019) to extract parameters of Mean Canopy Surface Height, Sum of Voxels and Canopy Surface Structure as described by (Schulze-Brüninghoff *et al.*, 2020). Hyperspectral data for each spectral band was averaged for each 1m² subplot and the spectral curves were afterwards normalized by vector normalization. Random forest regression was used to develop biomass estimation models with laser and hyperspectral parameters as independent features, each separately and in combination. To eliminate irrelevant features from the model input, function VSURF from R-Package VSURF (Genuer *et al*., 2019) was run. Training and test data selection (80% to 20%) was done randomly and repeated 100 times to reduce the impact of biased sample distribution for the model calibration. Model performance was evaluated by the coefficient of determination ($R^2$) and the normalized root mean square error (nRMSE) normalized by range of observations. The impact of the included features on the biomass model was interpreted with ALE plots (Accumulated Local Effects), which avoid mixing the effect of a feature with the effect of all correlated features, as correlated features do not have inevitably an effect on the prediction value (Apley & Zhu, 2019).

## Results and discussion

A combination of hyperspectral and 3d laser features gained the highest model performance up to $R^2$ 0.80 and nRMSE 12.0 % for FMY and $R^2$ 0.81 and nRMSE 12.1 % for DMY.

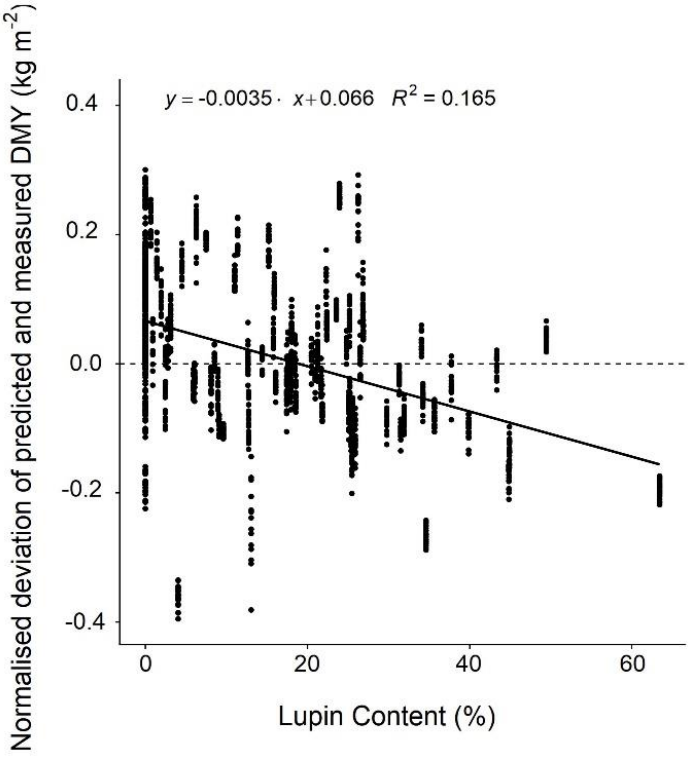


Figure 1. Random forest regression model: Normalised deviation between predicted and measured FMY and DMY for different contribution of lupin at each reference plot from lupin-invaded grassland sites with hundred different model runs.

Normalized deviation between predicted and measured biomass showed some overestimation for samples with low lupin contributions and, *vice versa*, underestimation for high lupin contributions. Between 20% and 40% of lupin contribution, the prediction model showed the lowest normalized deviation.

Feature selection process reduced the fusion model from 307 to a total number of 16 and 29 features for FMY and DMY prediction models. Both selections included laser as well as hyperspectral features. Most important features for FMY sensor fusion models were mean canopy surface height features, as well as wavelength between 845 nm and 858 nm. For DMY prediction models, the most important features were the mean elevation of the canopy surface, wavelength in the near infrared region, as well

as canopy surface height features. This shows that 3d point cloud information is ideally used with a multitude of different features. The important wavelength in the near infrared is known for its sensitivity to vegetation biomass. ALE plots showed positive correlation between the intensity of wavelength at 850 nm and the prediction of FMY. In addition, for DMY prediction the ALE plot showed a negative correlation with the reflectance at 946 nm. As this band is near to the minor water absorption band at 970 nm, the wavelength could probably indicate canopy water content. As DMY is the difference of FMY and canopy water content, DMY could be predicted by wavelength near the water absorption bands and features sensitive for FMY.

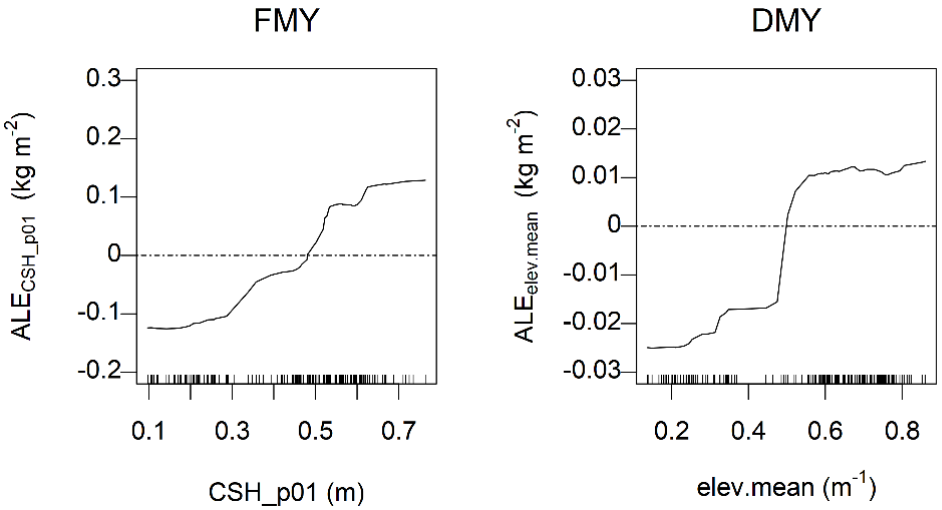


Figure 2. Accumulated Local Effects (ALE) plots of each hundred FMY (left) and DMY (right) sensor fusion models. Shown are the main effects (differences in prediction) of the most important features. ALE curves are calculated as median curve from each 100 model runs. Rug plots visualise the distribution of the feature values from each training data set, where each tick represents one of the 130 training samples (80% of all samples) for all 100 model runs (13.000 ticks).

## Conclusions

The combination of complementary sensor systems can increase the performance of biomass estimation on extremely heterogenous, extensive grasslands. Such methods may allow the replacement of labour-intensive, traditional biomass estimation in the future. The lowest over- and underprediction was found with lupin contributions between 20 and 40%. It could be shown that the abundance of invasive species can impact the prediction quality of remote sensing-based FMY and DMY prediction in grasslands.

## Acknowledgements

The study was funded by the German Federal Environmental Foundation (DBU: Deutsche Bundesstiftung Umwelt).

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# Using polygon grids to upscale ultra-high resolution UAV data for monitoring pastures

Bareth G. and Hütt C.

*GIS & RS Group, Institute of Geography, University of Cologne, D-50923 Cologne, Germany*

## Abstract

UAV imaging provides data in ultra-high spatial resolution of smaller than 3 cm. Although such data contains valuable information such as green cover and sward height, lower resolutions of e.g. 0.5 m meet the demands of monitoring pasture biomass or quality for management purposes. In the spatial analysis workflow of field experiment data, zonal statistics are essential to analyse and summarise UAV-derived data for individual plots or repetitions. Based on this concept, Bareth *et al*. (2016) proposed using polygon grids as zones input for zonal statistics on the field level. In this contribution, we (i) introduce the UAV data acquisition of a pasture experiment of the "GreenGrass" project which is funded by the BMBF, (ii) present UAV-derived sward growth data and the RGB vegetation index (RGBVI) in ultra-high spatial resolution (< 3 cm), and (iii) upscale sward height and RGBVI data using a polygon grid of 0.5 m.

**Keywords:** UAV, forage, biomass, quality, upscaling, grassland

## Introduction

Rango *et al*. (2009) investigated the promising potential of UAV-based monitoring for rangelands. A similar study was conducted by Bernie *et al.* (2009) for agricultural applications. The future potential of multi-sensors systems was summarized by Bareth *et al* (2011). Latest studies confirm the suitability of UAV-based sensor systems for monitoring grasslands (Bareth and Schellberg, 2018; Capolupo *et al*., 2015; Jenal *et al*., 2020; Lussem *et al.*, 2020; Näsi *et al*., 2018; Wijesingha *et al*., 2020). While such UAV sensing systems enable data acquisition in a spatial resolution of smaller than 3 cm, for management purposes spatial resolutions of 0.5 m to 2 m seem to be sufficient. However, the ultra-high spatial resolution contains essential information on the spatial variability of sward height, quality, and cover. In general, for upscaling of such ultra-high resolution image data, so-called resampling methods are applied which lose important information. In contrast, zonal statistics are computed on the single plot level for field experiment investigations (Bareth *et al*., 2016). The advantages of zonal statistics are that descriptive statistics (min, max, range, mean, std, sum) or even complete histograms can be computed for each single zone. Therefore, Bareth *et al*. (2016) proposed the use of spatially continuous polygon grids as zones to compute zonal statistics on the field scale. The objective of this study is the investigation of a 0.5 m polygon grid for upscaling ultra-high resolution UAV image data for a grazing experiment.

## Materials and methods

In 2020, the UAV campaigns were conducted at the pasture field experiment "Forbioben" which is operated by the Institute of Grassland Science at the Georg-August-University Göttingen. The grazing experiment is described in detail by Tonn *et al*. (2019). For the UAV data acquisition, a DJI Phantom 4 RTK (P4RTK) was used. The P4RTK is equipped with a 1" CMOS sensor capturing RGB images with 20 megapixels. Stereo photogrammetric analyses using Structure from Motion and Multiview Stereopsis (SfM/MVS) were done with Agisoft Metashape. For sward growth analysis, the Digital Surface Models (DSM) were analysed in ESRI's ArcGIS. The vegetation index RGBVI was computed from the RGB orthophoto and the 0.5 m polygon grid was generated in ArcGIS.

## Results and discussion

In Figure 1, the 9 ha grazing experiment, the 0.5 m polygon grid, and the upscaling results of sward growth and RGBVI are shown. Spatial resolution of the orthophoto is 1.2 cm.

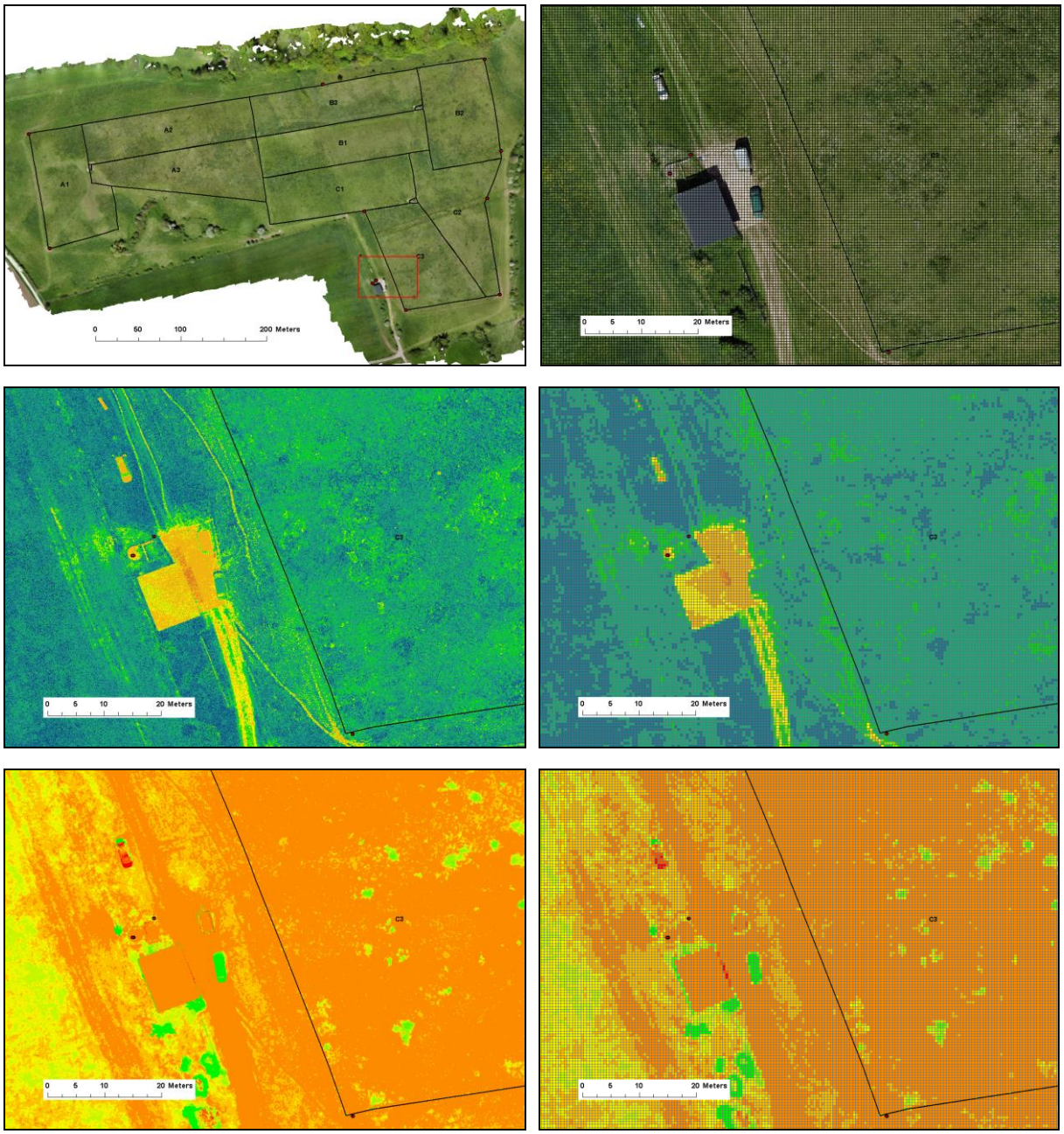


Figure 1. The upper left image shows a UAV-derived orthophoto of the “Forbioben” experiment on 6 May 2020. The upper right image displays the red marked rectangle in the upper left image including the 0.5 m polygon grid. The middle left image represents the computed RGBVI analysis in a full spatial resolution of 1.2 cm, while the middle right image shows the mean RGBVI values for the polygon grid. In the lower left image, sward growth is displayed in full spatial resolution of 2.4 cm, while the lower right image shows the zonal statistics data of the mean sward growth for the 0.5 m polygon grid.

It is clearly visible from the results presented in Figure 1 that the upscaling of UAV data in ultra-high spatial resolution (< 3 cm) using a 0.5 m polygon grid keeps characteristic spatial patterns of sward growth and spectral spatial patterns (RGBVI) without losing all valuable information. Descriptive statistics or even histograms are stored and can be utilized in a new way of information retrieval for the sward's structural and spectral characteristics. In the presented example, for each polygon grid cell of 0.5 m by 0.5 m, zonal statistics were computed from approx. 1,700 pixels. In total, zonal statistics were computed for more than 360,000 polygon grid cells covering the 9 ha of the grazing experiment. However, a clear drawback is the computational time, but it could be decreased in case of applying even larger polygon grids (e.g. 4 m or 10 m).

## Conclusions

As input for GIS-based analysis of zonal statistics, polygon grids serve as a promising approach for upscaling UAV data in ultra-high spatial resolution. Polygon grids even bear the potential of upscaling such data on the resolution of satellite data like Planet or Sentinel-2.


## Acknowledgements

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# Use of Sentinel-2 images for biomass assessment in extensive pastures in the Apennines (Central Italy)

Bellini E.[1], Argenti G.[1], Moriondo M.[2], Staglianò N.[1], Pugliese C.[1], Confessore A.[1], Aquilani C.[1], Nannucci L.[1], Bozzi R.[1] and Dibari C[1].

*DAGRI – Università degli Studi di Firenze, Italy; [2]Institute of BioEconomy – National Research Council, Italy*

## Abstract

The monitoring of forage production is one of the most important activities for establishing correct pasture management. Since above-ground biomass estimation with in-field traditional methods is costly in time and money, remote sensing techniques have been largely utilized and improved over the last decades to monitor grass growth and forage production. In this trial, we tested the potential of satellite-based vegetation indices (NDVI, SAVI, PVR, GLI, TVI, VARIGreen) in detecting actual pasture production, in terms of fresh biomass and dry matter over extensive grazing systems. Biomass was harvested from plots of 1m$^2$-surface wide (8 replicates per each study site) in two areas of Tuscany (Central Italy). The vegetation indices were elaborated from Sentinel-2 satellite images, acquired in correspondence of the sampling dates, and then correlated to pasture production measured from ground surveys. Best results in estimating fresh and dry forage biomass were achieved respectively with NDVI ($R^2$ = *0.*59) and SAVI ($R^2$ *=0.49*) but also other indices calculated from bands within the visible spectrum showed similar results in above ground biomass estimation.

**Keywords:** satellite, above ground biomass, remote sensing, pasture management, vegetation indices

## Introduction

Remote sensing techniques have proven to be consistent, cost-effective and reliable as a methodology for acquiring data and observing vegetation growth and development, and for providing useful indications in decision-making processes of agricultural management (Hatfield *et al*., 2019). Remote sensing applications are based on the use of vegetation indices (VIs), strongly related to vegetation features (e.g. LAI, biomass, health, canopy height, quality, etc.), derived from the combination of different waveband reflectance values captured from specific sensors (Xue and Su, 2017). In this context, satellite imagery has been widely applied in grassland studies to perform assessment of pasture production and forage quality (e.g. Serrano *et al*., 2019; Lugassi *et al*., 2019; Askari *et al*., 2019). The objective of this study is to determine the performance of different vegetation indices derived from Sentinel-2 in assessing above ground biomass of extensive mixed pastures over the grazing season.

## Materials and methods

The trial was conducted in two pastures (S1 and S2) in the Apennines (Central Italy), selected for different climatic conditions, altitude (200 m and 600 m asl) and botanical composition. Both sites were grazed by Limousin cattle for a large part of the experiment. In each site, samples of aboveground biomass from 1 m$^2$-plots (8 replicates per each study site, randomly distributed) were collected over the grazing season from 9 field-surveys (5 for S1 and 4 for S2). For the elaboration of the VIs, Sentinel-2 (Level 2A) images were acquired in correspondence with the sampling dates. These products, downloaded as atmospherically corrected, provide a 5 day-temporal resolution and a 10-m spatial resolution for reflectance values in band 2 (Blue), band 3 (Green), band 4 (Red) and band 8 (NIR). The VIs (Table 1) utilized in this trial were: NDVI, SAVI, PVR, GLI, TVI and $VARI_{GREEN}$. GLI original formula was modified (Band 4 instead of Band 5) to obtain the VI at higher spatial resolution (10 m-resolution of band 4 versus 20 m-resolution of band 5). Then, data on pasture production, in terms of fresh biomass (FB) and dry matter (DM), were correlated to the VI values. To achieve this result, for each sample point previously georeferenced, a buffer with a 10 m-radius was created in order to overcome possible issues related to geometric inaccuracy. Finally, the VI mean value, calculated from the values of each pixel inside the buffer, was correlated with the observed data for fresh and dry forage biomass (g·m$^{-2}$). This elaboration was performed with the GIS software QGIS and Semi-Automatic Classification Plug in.

Table 1. Vegetation indices utilized in the trial (see Sonobe *et al.*, 2018).

| | |
|---|---|
| NDVI (Normalized Difference Vegetation Index) | $(R_{NIR} - R_R) / (R_{NIR} + R_R)$ |
| SAVI (Soil-Adjusted Vegetation Index) | $(R_{NIR} - R_R) * (1+0.5) / (R_{NIR} + R_R + 0.5)$ |
| PVR (Photosynthetic Vigour Ratio ) | $(R_G - R_R) / (R_G + R_R)$ |
| GLI (Green Leaf Index) | $(2 R_G - R_R - R_B) / (2R_G + R_R + R_B)$ |
| TVI (Transformed Vegetation Index) | $\sqrt{NDVI + 0.5}$ |
| $VARI_{GREEN}$ (Visible Atmospherically Resistant Index) | $(R_G - R_R) / (R_G + R_R - R_B)$ |

## Results and discussion

Results of VI-Fresh biomass (FB) and VI-Dry matter (DM) regressions are shown in Tables 2 and 3. For each test site, higher $R^2$ values were achieved for FB assessment compared to DM-VIs regression. Considering the entire dataset (Total), best results in FB and DM were found, respectively, with NDVI ($R^2=0.59$) and SAVI ($R^2=0.49$), but also the other VIs reached similar $R^2$ values. As highlighted in Tables 2 and 3, better results of $R^2$ were generally obtained for S1. This can be probably explained by the specific botanical conditions of the two test sites. The first, S1, is an artificial pasture sown one year before the test, homogenous in terms of botanical composition, whereas S2 is a grassland sown several years before, with a high level of colonization of spontaneous species and with a considerable presence of shrubs, such as *Rubus ulmifolius*. As a result of distinctive spectral signatures between grasses and shrubs (Bayle *et al*., 2019), the diverse botanical compositions of the pastures probably led to differences between S2 and S1 in estimation of FB and DM.

Table 2. $R^2$ values and equations resulted from VI-Fresh Biomass (FB) regressions for Site 1 (S1), Site 2 (S2) and Total (Tot).

| Vegetation Index | $R^2$ S1 | Eq. S1 | $R^2$ S2 | Eq. S2 | $R^2$ Tot | Eq. Tot |
|---|---|---|---|---|---|---|
| NDVI | 0.66 | $y = 1.0857e^{7.6547x}$ | 0.52 | $y = 4.2926e^{6.076x}$ | 0.59 | $y = 1.9418e^{7.0005x}$ |
| SAVI | 0.63 | $y = 3.3115e^{8.4554x}$ | 0.51 | $y = 5.4321e^{7.952x}$ | 0.58 | $y = 3.9136e^{8.3455x}$ |
| PVR | 0.58 | $y = 72.929e^{8.2141x}$ | 0.59 | $y = 119.19e^{6.3312x}$ | 0.57 | $y = 91.357e^{7.3231x}$ |
| GLI | 0.66 | $y = 24.821e^{11.069x}$ | 0.48 | $y = 53.288e^{8.8288x}$ | 0.57 | $y = 34.692e^{10.135x}$ |
| TVI | 0.65 | $y = 3E\text{-}06e^{16.511x}$ | 0.51 | $y = 0.0003e^{12.787x}$ | 0.58 | $y = 2E\text{-}05e^{14.931x}$ |
| $VARI_{GREEN}$ | 0.55 | $y = 75.333e^{5.3969x}$ | 0.62 | $y = 119.27e^{4.1059x}$ | 0.57 | $y = 93.495e^{4.7466x}$ |

Table 3. $R^2$ values and equations resulted from VI-Dry Matter (DM) regressions for Site 1 (S1), Site 2 (S2) and Total (Tot).

| Vegetation Index | $R^2$ S1 | Eq. S1 | $R^2$ S2 | Eq. S2 | $R^2$ Tot | Eq. Tot |
|---|---|---|---|---|---|---|
| NDVI | 0.56 | $y = 0.6981e^{6.5362x}$ | 0.46 | $y = 4.2427e^{4.6143x}$ | 0.48 | $y = 1.4848e^{5.7603x}$ |
| SAVI | 0.52 | $y = 1.8933e^{7.129x}$ | 0.50 | $y = 4.161e^{6.4284x}$ | 0.49 | $y = 2.4644e^{7.0059x}$ |
| PVR | 0.47 | $y = 25.942e^{6.8499x}$ | 0.49 | $y = 54.473e^{4.6216x}$ | 0.44 | $y = 36.211e^{5.852x}$ |
| GLI | 0.55 | $y = 10.401e^{9.3067x}$ | 0.39 | $y = 30.217e^{6.4531x}$ | 0.44 | $y = 16.652e^{8.1146x}$ |
| TVI | 0.56 | $y = 1E\text{-}05e^{14.133x}$ | 0.45 | $y = 0.0025e^{9.7632x}$ | 0.47 | $y = 0.0001e^{12.325x}$ |
| $VARI_{GREEN}$ | 0.44 | $y = 26.677e^{4.4961x}$ | 0.50 | $y = 54.468e^{2.9997x}$ | 0.44 | $y = 36.81e^{3.8026x}$ |

## Conclusions

The results of the trial highlight the suitability of vegetation indices derived from Sentinel-2 in detecting FB and DM of multispecies pastures, especially in those characterized by homogeneity in botanical conditions, as S1. VIs based on NIR reflectance (i.e. SAVI, NDVI, TVI) and those based only on reflectance in the visible spectrum (PVR, GLI, $VARI_{GREEN}$) indicates similar results. Subsequently, their

potentiality in pasture biomass assessment, both for FB and DM, could be tested in sites with different vegetation conditions (e.g. botanical composition and shrub coverage) and further investigated by using images at finer spatial resolution by means of low-cost Unmanned Aerial Vehicle (UAV) or RGB cameras installed in pastures proximity. Employment of these remote sensing techniques seems to open new perspectives in pastoral resources planning.

## Acknowledgement

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# A tool to select the best parental genotypes by combining lab and field tests

Statkevičiūtė G., Kemešytė V., Aleliūnas A. and Jaškūnė K.

*Institute of Agriculture, Lithuanian Research Centre for Agriculture and Forestry, Instituto a. 1, LT-58344 Akademija, Lithuania*

## Abstract

Highly productive forage grass cultivars capable of withstanding water shortage without suffering huge yield penalty are a desirable outcome of any breeding programme. In this study we propose a water deprivation tolerance in combination with leaf growth under controlled conditions and plant yield under field conditions as a tool to select superior genotypes to be used as parent plants in pre-breeding. A panel of 107 perennial ryegrass ecotypes, mostly originating from Lithuania and Ukraine, were used. Leaf elongation was measured using a phenotyping platform, designed to track it with high temporal resolution. Tolerance was calculated as a measure of time span between the points when the plant reduces growth and arrests it under water stress. There was a moderate correlation ($r$ = 0.41, $P$ < 0.05) between leaf elongation under optimal conditions and tolerance, indicating the presence of fast growing and stress-tolerant plants in the panel. Analysis of these traits in combination with dry matter yield allowed us to pinpoint genotypes that can be used as stress tolerance donors in the crosses with superior cultivars without reducing the yielding capacity of the offspring.

**Keywords:** dry matter yield, perennial ryegrass, pre-breeding, water deprivation

## Introduction

Plant breeding aimed at improving perennial ryegrass dry matter yield has led to a 3.2% increase per decade (Sampoux *et al*., 2011). However, under climate change, temperate regions face mild summer droughts which reduce yield and escalate crop demand. Therefore, drought tolerance research has received increasing attention to understand the mechanisms causing yield loss. High forage yield and quality makes perennial ryegrass (*Lolium perenne* L.) the predominant forage grass species known for its rapid response to drought because it requires a relatively large amount of water to sustain growth (Norris, 1985). Mild drought does not threaten the survival; however, plant growth slows down before leaf water content decreases, leading to reduced biomass accumulation, which is the main yield target in forage crops (Jaškūnė *et al*., 2020). Biomass accumulation is mainly determined by leaf growth, the effect of water limitation on its growth could be used as a diagnostic tool to assess drought tolerance of the plant. From a breeder's perspective, combining elite genotypes having high growth rate with an ecotype responding late to water stress could result in a high yielding drought-tolerant cultivar. The aim of the study was to broaden the genepool in pre-breeding programs by identifying fast growing and high yielding ecotypes exhibiting superior tolerance to mild drought.

## Materials and methods

A perennial ryegrass panel, consisting of cultivars and ecotypes, was investigated in the field and controlled environment trials. A subset of 107 perennial ryegrass ecotypes, originating from Lithuania (35), Ukraine (55), Latvia (2), Poland (2), Slovakia (2), Denmark (1), and Russian Kaliningrad region (10) were used in this study. The growing leaf was attached to a string and kept taut while plastic beads threaded onto the string and placed on the growth array provided landmarks for image-based tracking. Images of the growth array were taken every 2 min and analysed with the LLT software. To induce a water deficit stress, plants were deprived of water for 130 h. Soil moisture was measured every 4 h using integrated sensors. Drought tolerance was calculated using Tri-Phase function as described in Yates *et al*. (2019). Detailed descriptions of the genotypes and leaf growth tracking method are presented in Jaškūnė *et al*. (2020). The field experiment was performed at LAMMC Institute of Agriculture (55°40 N, 23°87 E) in 2013 and 2014. Single plants were planted at 50 × 50 cm distances using a randomized complete block design with 4 replications. Dry matter yield per plant was determined as described in Statkevičiūtė *et al*. (2015). Statistical analysis was implemented in the open-source R statistical environment v.4.0.2 (R Core Team, 2020).

## Results and discussion

Even though dry spells are becoming more common in Lithuania during the vegetation season, weather conditions during 2013 and 2014 did not provide the possibility to assess tolerance to water deprivation of the genotypes. Mean dry matter yield per plant (DMY) varied significantly between the years (83.2 g ± 28.8 in 2013; 178.5 g ± 66 in 2014), and it was most likely affected by different overwintering conditions and weather temperatures in spring. The mean leaf growth rate was 0.061 ± 0.021 $mm.h^{-1}.{}^{\circ}C^{-1}$ and mean tolerance was 1.47 ± 0.68 log10 (hPa) (Table 1).

Table 1. Phenotypic traits of perennial ryegrass ecotypes (mean ± sd).

| Trait | Ukrainian origin n = 55 | Lithuanian origin n = 35 | Russian origin n = 10 | Other n = 7 |
|---|---|---|---|---|
| Dry matter yield 2013, g | 75.2 ± 26.98 | 93.43 ± 27.15 | 76.37 ± 37 | 76.37 ± 34.45 |
| Dry matter yield, 2014, g | 199.73 ± 62.51 | 155.0 ± 61.28 | 130.91 ± 50.46 | 130.91 ± 50.46 |
| Leaf growth rate, $mm.h^{-1}.{}^{\circ}C^{-1}$ | 0.06 ± 0.02 | 0.06 ± 0.03 | 0.06 ± 0.02 | 0.06 ± 0.03 |
| Tolerance, $log_{10}$ (hPa) | 1.47 ± 0.63 | 1.35 ± 0.70 | 1.58 ± 1.09 | 1.58 ± 1.09 |

There was no correlation between tolerance and DMY, which was not surprising as plants did not experience water shortage in the field experiment. There was also no correlation between leaf growth rate and DMY. However, plants seldom experience ideal growing conditions in the field; moreover, leaf growth, even though an important factor, does not determine the yield alone, as traits such as tiller number, leafiness etc. also come into play. A moderate correlation ($r$ = 0.41, $P$ < 0.05) was calculated between leaf growth rate under optimal conditions and drought tolerance. Wild genotypes usually are not high-yielding and are employed in pre-breeding as donors of stress resistance; however, productive genotypes can also be found in natural environments (Bachmann-Pfabe *et al.*, 2018). The combination of field DMY data with drought tolerance in PCA analysis enabled us to pinpoint the genotypes superior in both traits, as well as discard those that were high yielding, but likely to perform poorly under water deficit stress. Genotype No 47 stood out (Figure 1) by all measured traits.

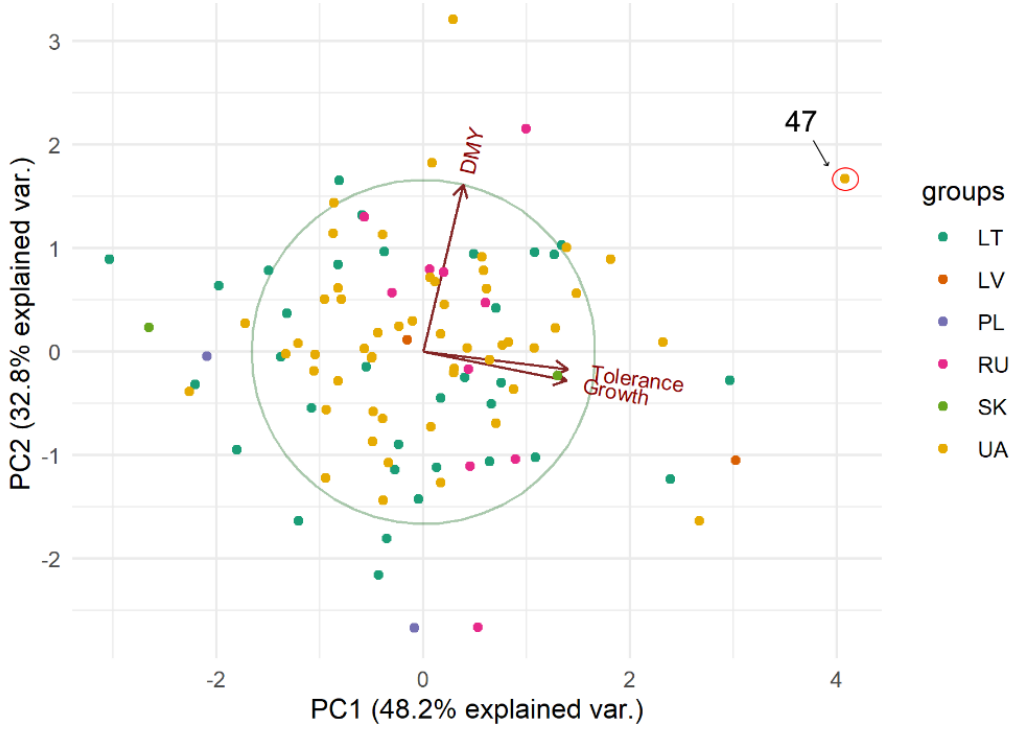


Figure 1. Principal component analysis of wild ecotypes based on leaf growth rate and water deprivation tolerance assessed under controlled conditions and mean dry matter over two years of the field experiment.

Its mean DMY was 215 g, leaf growth 0.11 $mm.h^{-1}.{}^{\circ}C^{-1}$ and tolerance 3.5 $\log_{10}$ (hPa). For comparison, five fastest growing forage genotypes produced DMY of 108 ± 28 g, their mean leaf growth was 0.12 ± 0.02 $mm.h^{-1}.{}^{\circ}C^{-1}$ and mean tolerance was 1.4 ± 0.8 $\log_{10}$ (hPa). Therefore, this wild ecotype outperformed the best forage genotypes in DMY, exhibited similar leaf growth rate and was more tolerant to water deprivation, indicating it can be a valuable parent in the forage breeding programmes.

## Conclusions

The results of the study confirm that natural ecotypes are not only a source of stress resistance but can possess high yielding potential. Though the plants were evaluated under non-stress conditions in the field, combining the field and lab test enabled us to identify high yielding and drought-tolerant genotypes.


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# Estimating standing biomass of sown biodiverse pastures using a combination of remote sensing and machine learning

Morais T.G.[1], Jongen M.[1], Rodrigues N.R.[2], Gama I.[2], Domingos T.[1] and Teixeira R.F.M.[1]

*[1]MARETEC – Marine, Environment and Technology Centre, Instituto Superior Técnico, Universidade de Lisboa, Av. Rovisco Pais, 1, 1049-001 Lisbon, Portugal; [2]Terraprima – Serviços Ambientais, Lda., 2135-199 Samora Correia, Portugal*

## Abstract

Beef cattle production in Alentejo (Portugal) is based on a mixture of grazing and supplementation. Sown biodiverse permanent pastures rich in legumes (SBP) provide quality animal feed, offset concentrate consumption and increase carbon sequestration. Providing estimations of biomass in SBP is critical for optimizing their use by farmers. We developed data processing and calibration algorithms based on remote sensing (RS) and machine learning (ML) to estimate pasture biomass. RS data were acquired from Sentinel-2 (S2). Five additional vegetation indices were calculated from the individual bands of S2. Calibration data were collected in spring 2018 and 2019 on farms. The ML method used was random forest (RF). A multi-group cross-validation approach was used, where each group is a unique combination of farm and year; in total 9 groups were considered. We used this approach to assess the estimation error when the model is applied to a new farm and year that was not used in training. Results demonstrate good predictive capacity, with root mean squared error of 810 kg DM $ha^{-1}$ (average biomass equal to 2,499 kg DM $ha^{-1}$) and an $r^2$ higher than 0.6. This approach can lead to expedited and low-cost mapping of biomass in SBP.

**Keywords:** pastures, Sentinel-2, random forest, cross-validation

## Introduction

Portuguese sown biodiverse pasture (SBP) have multiple positive effects that stem from the increase in productivity (in comparison with semi-natural pastures) and the higher quantity and quality of animal feed (Morais *et al*., 2018; Teixeira *et al*., 2018). These pastures are a mixture of up to 20 species or varieties of legumes and grasses. The main environmental co-effect of increased productivity in SBP is the increase in soil organic matter (SOM) (Teixeira *et al*., 2011), which translates into carbon storage and consequent sequestration from the atmosphere. However, field surveys quantifying these effects still rely on field-based/destructive methods that involve cutting the grass in the field to determine yields and, for SOM, require laboratory analysis. Those methods are time expensive and require significant labour effort (Sinha *et al*., 2015). In order to avoid these drawbacks, alternative methods have been proposed in recent years, namely the use of remote sensing (RS) data. In the last decade, the development of space-borne sensors in spatial and temporal resolutions brought forward RS as a powerful tool for large-scale monitoring (Ali *et al*., 2016). In this study, we used Sentinel-2 (S2) spaceborne data in combination with the random forest (RF) algorithm for the estimation of standing biomass in SBP. A cross-validation was also performed in order to assess more accurately the estimation error.

## Materials and methods

Biomass samples were collected between February and May of 2018 and in February 2019 from six farms located in south and central Portugal. In each farm, 24 plots were sampled, but on each collection date not all plots were sampled and the number of samples per plot also varied, e.g. in Farm 1, all the plots were sampled in April 2018 and only 8 plots were sampled in February and May 2018. In total, for soil and biomass, 254 and 242 samples, respectively, were collected. Each collection sample covered an area of 0.04 $m^2$.

S2 data were collected with the most similar date to the date of field collection of samples for calibration, and five vegetation indices were calculated (NDVI, NDWI, SR, SAVI and OSAVI). We considered also seven additional covariates depicting (i) the weather, through the daily average temperature, accumulated precipitation and accumulated radiation since September 1$^{st}$; and (ii) the terrain, through elevation, slope and land morphology (which distinguishes between water accumulation and water

runoff areas), and finally an auxiliary variable, the number of days since the beginning of the production year, which was assumed to be September 1st of the previous year.

For RF models, in order to find the hyperparameters that lead to the best performance, we used a Bayesian optimization approach. In the Bayesian search, we considered the number of trees (between 1 and 1000), minimum number of samples per leaf (between 1 and 50), the maximum depth (between 1 and 100), the error function (mean squared error or mean absolute error), maximum number of features/inputs (all inputs, the squared root of the total inputs and the log2 of the total inputs) and the use of a bootstrap approach (categorical: yes or no).

A cross-validation approach was used with 9 groups, where each group is a unique combination of farm and year (e.g. “Farm 1-2018” is one group and “Farm 1-2019” is another group). We used this approach to assess the estimation error (RMSE) when the model is applied to a new farm and year that was not used in training.

## Results and discussion

Figure 1a presents the boxplot for standing biomass and the nine groups. The average standing biomass was 2,499 kg DM $ha^{-1}$ among all the collected samples (n=242). Standing biomass was similar in both production years: 2,402 kg DM/ha in 2018 and 2,583 kg DM $ha^{-1}$ in 2019. The Farm 2-2019 group had the highest average biomass and the Farm 3-2018 had the lowest biomass: 3,286 and 1,746 kg DM $ha^{-1}$, respectively. The maximum standing biomass was 8,096 kg DM $ha^{-1}$ (Farm 1-2018, May) and the minimum standing biomass was 238 kg DM/ha (Farm 3-2018, February). The Farm 2-2019 was the group with the highest variation between the samples and the group Farm 3-2018 was the one with the lowest variation, the interquartile distance being 3,087 kg DM/ha and 767 kg DM $ha^{-1}$, respectively.

Figure 1b presents the estimated standing biomass as function of the observed values. In each group, the represented estimated values were obtained from the group where the sample of those groups were not used to train the model. Estimation error (RMSE) is highly dependent on the group. The average RMSE is 810 kg DM $ha^{-1}$ ($r^2$ is equal to 0.63). RMSE ranges between 510 kg DM $ha^{-1}$ (Farm 5-2019 – represented in light blue in Figure 1b) and 1,325 kg DM $ha^{-1}$ (Farm 1-2019 – represented in orange in Figure 1b). The use of covariates reduced the RMSE of the obtained models by 20% in comparison with a model without covariates.

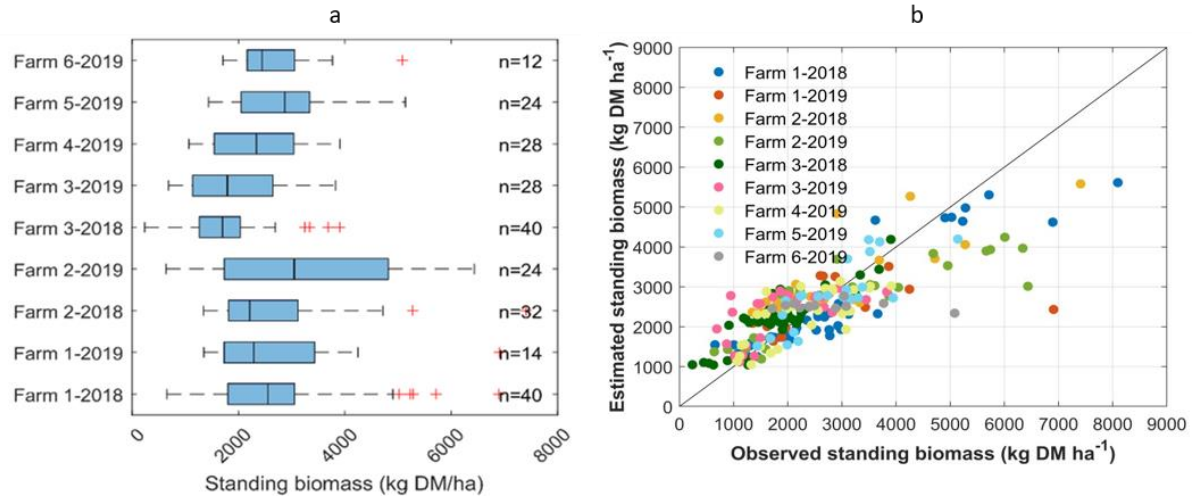


Figure 1. Boxplot and the estimated standing biomass of standing biomass per group (unique combination of farm and year)

Estimation error is higher in the samples with the highest standing biomass. For measured values higher than 5,000 kg DM $ha^{-1}$ the obtained model has a systematic underestimation, namely in the Farm 1-2018 (dark blue in Figure 1b). Further, Farm 1-2018 is also the second group with highest number of samples (40 samples), thus when the samples from this group are not used to train the model, the obtained model was unable to estimate high standing biomass values. The obtained model is also particularly poor at estimating the standing biomass of Farm 6-2019.

## Conclusions

This work shows that standing biomass of SBP can be accurately estimated through the combination of RS data and ML models (RMSE: 810 kg DM $ha^{-1}$; $r^2$: 0.63). We also included seven context variables that usually are not taken into account in similar studies, depicting weather and morphology of the sampled plots, and showed their relevance in improving the results. Finally, we used a cross-validation approach (considering 9 validation groups) in order to have a better error estimation when the trained model is applied to a new farm and year.


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# Predicting herbage yield in perennial ryegrass breeding trials using UAV derived data and machine learning

Pranga J.[1,2], Borra-Serrano I.[1], Aper J.[1], Ghesquiere A.[1], Roldán-Ruiz I.[1,3], Janssens I.[2], Ruysschaert G.[1] and Lootens P.[1]

*[1]Plant Sciences Unit, Flanders Research Institute for Agriculture, Fisheries and Food (ILVO), Melle, Belgium; [2]Department of Biology, University of Antwerp, Wilrijk, Belgium; [3]Department of Plant Biotechnology and Bioinformatics, Ghent University, Ghent, Belgium*

## Abstract

Several methods have been developed to estimate biomass yield in ryegrass using remotely sensed spectral and structural features. This study builds further upon procedures developed in the breeding programme of ILVO. In previous work, we focused on canopy height as the main predictor of yield. Here we investigate whether the prediction of herbage yield in perennial ryegrass can be improved using canopy height information combined with spectral bands captured using different sensors. We used six breeding trials comprising 115 diploid and 112 tetraploid varieties and populations, with a total of 468 plots. A series of UAV flights was carried out with two sensors, a 10-band multispectral and an RGB camera system. The acquired data were then used to estimate the yield of the first spring cut in May 2020. Repeated nested cross-validation allowed us to evaluate the performance of the predictive models. Three machine learning algorithms (Random Forest, Support Vector Machine and Partial Least Squares Regression) were applied, to better understand the applicability of those techniques for accurate yield assessments. This study provides new insights to ryegrass biomass estimation related to earliness and ploidy level.

**Keywords:** *Lolium perenne*, dry matter yield, RGB, multispectral, pasture, high throughput field phenotyping

## Introduction

State of the art (close) remote sensing technologies can be used to predict and monitor crop yield. In recent years there has been a growing interest in the development of UAV-based methods for non-destructive estimations of herbage yield in grasslands. Several studies have exploited the potential of different remotely sensed information, including spectral, structural (Lussem *et al*. 2019; de Alckmin *et al.*, 2020) and textural features (Grüner *et al.*, 2020). This study builds further upon the high throughput field phenotyping procedures developed for the perennial ryegrass (*Lolium perenne*) breeding programme of ILVO by Borra-Serrano *et al*. (2019) and Aper *et al*. (2019). While in these studies we demonstrated that canopy height (CH) is a good predictor of herbage yield, here we examine whether the prediction of herbage yield in perennial ryegrass can be improved using CH information combined with spectral data derived from different sensors.

## Materials and methods

A field trial established in May 2019 in Merelbeke (East Flanders, Belgium) was investigated. The trial comprises 115 diploid and 112 tetraploid varieties and populations of *Lolium perenne*, arranged in a randomized block design with two replicates. The trial was mown five times in 2020. Here, we focus on the spring cut carried out on 4 and 5 May 2020 with a grass plot harvester (Haldrup F-55, Haldrup, Denmark). Before the harvest, four consecutive UAV flights were performed (on April 1, April 15, April 23 and May 4). A UAV (M600, DJI, China) was used in combination with an RGB camera system (α6000, Sony Corporation, Japan) and a multispectral camera (Dual Camera System, Micasense, USA). The MS sensor includes ten bands: coastal blue 444, blue 475, green 531, green 560, red 650, red 668, red edge 705, red edge 717, red edge 740, and NIR 842 nm. RGB images were stitched using Agisoft Metashape Professional v1.5.5 (Agisoft, Russia), while multispectral images were processed with Pix4D Mapper 4.5.6 (Pix4D, Switzerland). For the processing of RGB images, we followed the workflow described in Borra-Serrano *et al*. (2019). Nine Ground Control Points (GCPs), measured on-site with an RTK GPS (Stonex S10 GNSS, Italy), were used for precise georeferencing. Geometrically corrected orthophotos, digital elevation models (DEMs) and reflectance maps were generated. As we have

demonstrated that inclusion of mean intensity leads to a substantial improvement of yield estimates (Aper *et al*., 2019), the orthophotos were transformed from RGB (red, green, blue) to HIS (hue, intensity, saturation) colour space using QGIS 3.12.3 with GRASS 7.8.3. software. For each plot we extracted the 25$^{th}$, 50$^{th}$ (median), and 75$^{th}$ percentiles from spectral variables. From the computed RGB based CH model the 90$^{th}$ percentile was also included. To model dry matter yield (target variable), five different feature combinations were selected. First, we built models with CH variables only. Then, CH data were combined with RGB, HIS and multispectral bands, separately. For the next two datasets, only spectral information from two different sensors was selected. Models were built separately for diploids and tetraploids. We applied three machine learning algorithms, including Random Forest (RF), Support Vector Machine (SVM), and Partial Least Squares Regression (PLSR), to predict dry matter yield. Five times repeated nested cross-validation (CV), with 10-fold in the outer and 5-fold in the inner CV loop was implemented. The outer resampling loop was utilised to estimate the generalisation performance, quantified using relative root mean squared error (rRMSE). We applied the *mlr* package within R v4.0.2 using RStudio v1.3.1093 (RStudio: IDE for R, R Studio Inc., USA) for statistical modelling.

## Results and discussion

The highest production of forage biomass is realised during the spring cut of perennial ryegrass. In this experiment the total dry matter yield varied between 2.3 and 6.5 Mg ha$^{-1}$ for diploids and between 3.6 and 7.6 Mg ha$^{-1}$ for tetraploids. Thus, on average tetraploids produced more biomass than diploids. Preliminary analysis of the model performance estimates (Figure 1) show that for diploids the CH information already resulted in a low rRMSE compared to using or combining these data with spectral information (lowest mean *rRMSE = 10.4%*). For tetraploids using or adding spectral information to the CH data slightly improved model performance compared to dataset with CH data only (lowest mean *rRMSE = 9.1%*). No clear advantage of one machine learning algorithm over another was identified, when applied to the same dataset.

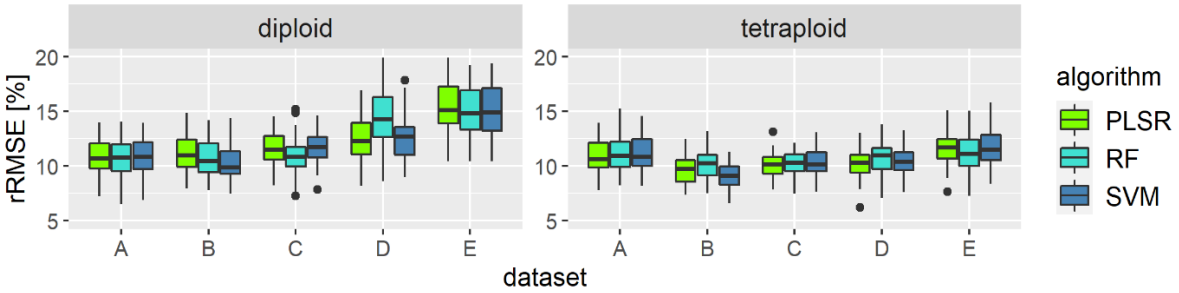


Figure 1. Box plot representing a distribution of model performance estimates (rRMSE), fitted by three different machine learning algorithms: PLSR, RF, and SVM. Dry matter yield (DMY) was set as a target variable, while (A) CH data; (B) CH combined with multispectral bands; (C) CH combined with RGB and HIS data; (D) multispectral bands; and (E) RGB and HIS data were set as predictor variables.

The findings of this study suggest that canopy height variables are a better predictor of herbage yield in diploids than in tetraploids, at least in the first cut of the year. A possible explanation might come from the growth characteristics of tetraploids. In a relatively high proportion of the tetraploid plots, 'bending' of the leaves was observed, what might have distorted canopy height measurements. The 'bending' plots showed a higher intensity and a lower saturation compared to diploid plots. Therefore, lower rRMSE could be reached for tetraploids including HIS colour space channels to the model (dataset E).

## Conclusions

In this investigation, the aim was to analyse the potential of using data acquired simultaneously using two different sensors for the herbage yield assessment. Biomass predictions of perennial ryegrass could be improved by combining CH information with spectral data. However, the improvement is more pronounced for tetraploids than for diploids. While previous studies generated variation in grass swards by different nitrogen fertilizer levels (de Alckmin *et al*., 2020; Lussem *et al*., 2019), in this study we focused on populations capturing a broad genetic and phenotypic variation. In the next phases of our research, we plan to incorporate the data obtained from other cuts and flight campaigns.

## Acknowledgements

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# Evaluation of a grassland drought index based on LAI from remote sensing and meteorological data

Peratoner G.[1], Greifeneder F.[2], Castelli M.[2], Crespi A.[2], Zellner P.J.[2], Vianello A.[2], Morlacchi M.[1], Pasolli L.[2], Bartkowiak P.[2], Notarnicola C.[2], Monsorno R.[2] and Zebisch M.[2]

*[1]Laimburg Research Centre, Vadena/Pfatten, I-39040 Ora/Auer, Italy; [2]EURAC research, Drususallee/Viale Druso 1, I-39100 Bozen/Bolzano, Italy*

## Abstract

Indices based on optical satellite remote sensing imagery have shown to be suitable for quantifying drought-related yield losses. The Forage-Production-Index (FPI), combining meteorological observations and remote sensing-based LAI retrievals from MODIS, was adapted for the application in South Tyrol (NE Italy) in a mountainous, highly heterogeneous landscape. Yield measurements from field trials covering 39 environments (site x year) were used for validation, which was performed using mixed models describing the relationship between dry matter yield and FPI (or their variation with respect to a reference period) and accounting for the design effects treated as random factors. Following variants in computing FPI were applied: spectral unmixing of LAI, correction by means of Water Stress Coefficient (CWS) and aggregation scale. The prediction ability of the index was found to be low. Unmixing and correction by CWS resulted in a minor improvement in accuracy. Possible reasons for the low sensitivity are: i) insufficient spatial resolution of MODIS satellite data with respect to the complexity of land use; ii) lack of coincidence between yield at validation sites and surrounding grassland; iii) small number of validation sites, possibly not covering the whole yield variation over the area and period investigated.

**Keywords:** MODIS, LAI, mountain environment, forage yield, parametric insurance, drought

## Introduction

According to the Rural Development Program of the European Commission (EC), it is no longer possible to compensate crop losses with public funds. To financially compensate for the damage suffered from extreme weather events, parametric insurance policies, or mutual funds, are a viable option to increase the economic sustainability of farms. This article presents preliminary results with challenges and lessons learned from implementing a drought index to identify grassland yield anomalies through satellite measurements and meteorological data, following the EC requirements. The strategy adopted was to adapt an existing index to the specific requirements of a mountainous area and to perform its calibration and validation based on time-series of yield measurements in the study area of South Tyrol in North-East Italy. Land use in the area is characterised by small-scale grassland-based farms and a topographically complex mountain environment.

## Materials and methods

For the mapping of grassland yield losses, the Forage-Production-Index (FPI) was selected. This index was developed by Roumiguié *et al.* (2015, 2017) for application in an agricultural insurance context and is currently used for insurance policies in France. The index relies on the estimation of biomass anomalies, based on remotely sensed Leaf-Area-Index (LAI), combined with the so-called Water-Stress-Coefficient (CWS), based on precipitation and reference evapotranspiration ($ET_0$). The estimation of LAI relied on data from the MODIS satellite mission. The following steps were applied: i) download of the MODIS products MOD/MYD09GQ-LG2 (red and near-infrared at 250 m spatial resolution) and MOD/MYD09GA-LG2 (blue and shortwave-infrared at 500 m);ii) MODIS pre-processing (acquisition geometry correction, 4-day temporal compositing, masking of clouds, shadows, and other low-quality acquisition); iii) spectral un-mixing; iv) retrieval of the LAI based on the inversion of the PROSAIL radiative transfer model (Jacquemoud *et al*., 2009); and v) daily interpolation of LAI. The calculation of the daily CWS relied on interpolated meteorological station measurements and downscaled Meteosat solar radiation maps. The anomalies ($\Delta$FPI) were defined as the ratio between $FPI_n$ and the Olympic average over the previous 5 years or over all available observation years (REF: oa = Olympic average; wp = whole observation period). For the sites with three observation years only, the average of three

years was used instead of the Olympic average. The FPI was evaluated considering the effect of the following processing steps: spectral unmixing of LAI in case of mixed pixels (SU: no = mixed; yes = unmixed), correction using CWS (CWSC: yes/no), and spatial aggregation scale (SAS: cc = pixel including the field trial used for validation, avg = mean of all pixels surrounding cc). Dry matter yield measurements (at 5 cm stubble height) from multiyear (3 to 13 years between 2004 and 2017) field trials on non-irrigated grasslands (5 experiments, years x sites = 39 environments) investigating different cutting frequencies combined with specific fertilisation inputs and three true replicates (16 m²-plots) per treatment were used as a reference. The predictive accuracy of FPI and ΔFPI was investigated with respect to forage yield and percent yield variation with reference to the same period used to compute ΔFPI, respectively. FPI was computed for all possible combinations of SU, CWSC, SAS and two different resolutions of yield data (RYD: tr = mean across treatments per site and year; pl = single plots) were analysed. Validation was performed using mixed models investigating the relationship between the respective vegetation index and annual yield. Site and design effects were treated as random effects. Where appropriate, the serial correlation of measurements on the same plot/site in different years was treated as repeated measurements with the plot/site as a subject. For FPI validation, only yield data obtained at the site-specific cut frequency were considered, whilst all investigated management intensities were included in the ΔFPI analysis. The squared correlation between observed and predicted values ($R^2$) was used to assess the prediction accuracy of each model.

## Results and discussion

$R^2$ values between 0.322 and 0.423 were obtained for the relationship between FPI and yield. For six of the 18 models, the *P*-value of FPI exceeded 0.05 and/or the 95% confidence interval of the slope included zero. Prediction accuracy seemed to be less affected by RYD (Figure 1a). Similarly, no apparent role was played by SAS, whilst SU and CWSC resulted in a mean $R^2$ increase of 0.03 (not significant) and 0.05, respectively. Much lower $R^2$ values were found for the relationship between ΔFPI and the percent yield variation (between 0.002 and 0.218). The same pattern already observed for the FPI-based models was found (Figure 1b) with SU and CWSC doubling accuracy (from 0.054 to 0.108 for SU and from 0.058 to 0.102 for CWSC).

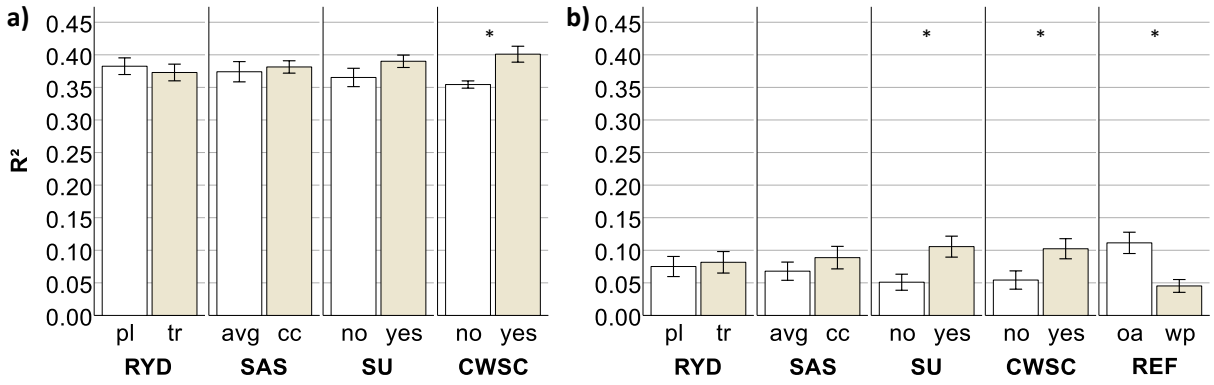


Figure 1. Comparison of prediction accuracy due to RYD, SAS, SU and CWSC for a) FPI and b) ΔFPI. Means across all factors ± standard errors are shown. The values are averages of 8 models for FPI and of 16 models for ΔFPI. Significant differences at $P<0.05$ by a t-test are flagged by an asterisk. RYD = resolution of the yield data (tr = mean across treatments per site and year; pl = single plots); SAS = spatial aggregation scale (cc = pixel including the field trial used for validation, avg = mean of all pixels surrounding cc); SU = spectral unmixing of LAI; CWSC = correction by means of CWS; REF = reference period (oa = Olympic average; wp = whole observation period).

Using the Olympic average also resulted in more than doubled $R^2$-values compared to using the whole observation period (0.119 vs 0.045). Possible sources of error explaining the low accuracy in comparison to previous research (Roumiguié *et al.*, 2017) are expected to be i) the insufficient spatial resolution of MODIS satellite data with respect to the complexity of land use (small-scale field structure, non-grassland land cover – only approximately 10% of MODIS pixels containing grassland can be considered pure – as well as noise due to heterogenous agronomic management) and the discrepancies between the cartographic support used to differentiate land use within each pixel (relevant for SU); ii)

the high heterogeneity of the areas surrounding the experimental sites, which causes the experimental data not to describe the yield of the surrounding grassland areas correctly; iii) the small number of validation sites, which probably do not cover the whole yield variation within the area and period investigated.

## Conclusions

The prediction accuracy of FPI on forage yield was found to be modest, whilst that of ΔFPI on percent yield variation (even if significant and with a slope >0) seems to be unsuitable for the implementation of an insurance system in the given context. Significant advances are expected soon due to the high-resolution data from the COPERNICUS programme, increasing the spatial representativeness of satellite-based LAI in heterogeneous regions. The collection of yield data matching the scale of remote sensing data and at a larger number of sites is expected to improve the reliability of the validation results.

## Acknowledgements

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# Validation of a workflow based on Sentinel-2, Sentinel-1 and meteorological data predicting biomass on pastures

Nickmilder C.[1], Tedde A.[1], Dufrasne I.[2,3], Lessire F.[3], Tychon B.[4], Curnel Y.[5], Bindelle J.[1] and Soyeurt H.[1]

*[1]TERRA Research Centre, Passage des Déportés 2, 5030 Gembloux, Belgium; [2]Centre des Technologies Agronomiques, rue de la Charmille, 16, 4577 Strée-Modave, Belgium; [3]ULiège, Quartier Vallée 2, avenue de Cureghem 6, 4000 Liège, Belgium; [4]ULiège, avenue de Longwy 185, 6700 Arlon, Belgium; [5]Centre wallon de Recherches agronomiques (CRA-W), Rue de Liroux, 9, 5030 Gembloux, Belgium*

## Abstract

This study develops the validation of the four best promising models resulting from a workflow processing Sentinel-1, Sentinel-2 and meteorological data through 13 different machine learning algorithms that led to 124 models predicting biomass under the form of compressed sward height on square sub-samples of paddocks (i.e., pixel-based estimation with a resolution of 10 m). The training and validation data were acquired in 2018 and 2019 in the Walloon Region of Belgium with a rising platemeter equipped with a GPS. The cubist, perceptron, random forest and general linear models had a validation root mean square error (RMSE) around 20 mm of CSH. However, the information relevant for the farmer and for integration in a decision support system is the amount of biomass available on the whole pasture. Therefore, those models were also validated at a paddock-scale using data from another farm (117 CSH records acquired with a different rising platemeter) based on input variables expressed at paddock scale or predictions aggregated at paddock scale. The resulting RMSE were higher than before. To improve the quality of prediction, a combination of the outputs of the models might be needed.

**Keywords:** compressed sward height, pasture, remote sensing, prediction, Sentinel, machine learning

## Introduction

Advantages of grazing in agroecosystems are well recognized: lower feeding cost (Hennessy *et al.*, 2020), higher animal welfare and increased milk quality (Elgersma, 2015). However, intensive dairy farmers turn away from grazing (Lessire *et al.*, 2019). One of the main reasons is the need for a frequent assessment of the available standing biomass. Decision support systems (DSS) were developed previously on the basis of mechanistic models (e.g. Romera *et al.*, 2010 and Ruelle *et al.*, 2018) to address this issue. Another approach to develop such DSS is the use of remote sensing. Recently, we described a framework to develop machine learning (ML) models using Sentinel-1 (S-1), Sentinel-2 (S-2) and meteorological (met) data to predict biomass under the form of compressed sward height (CSH) (Nickmilder *et al.*, 2021). Its application to data acquired over three farming areas located in Wallonia (southern Belgium) led to the choice of 4 promising models: a cubist, a generalized linear model with elastic regularization of the gaussian family (glmnet) and a random forest (rf) using 160 variables (26 met, 10 S1 and 124 S2) and a neural network (nnet) using 47 variables (9 met and 38 S-2). An analysis of the performances of these four models on an independent dataset is performed and presented here.

## Material and methods

The 117 validation CSH data were acquired with a Jenquip EC-01 in Eastern Wallonia on a weekly basis from May 2019 to October 2019 during farm walks on land parcels covering an area between 1.9 ha and 5.9 ha (Delhalle and Knoden, 2019). Some constraints decreased the amount of validation data: given that the four models integrated S-2, S-1 and met data, 28 records out of the 117 were discarded due to the presence of clouds making S-2 data unusable. Similarly to findings in our previous article, the predictions were either made on all the data aggregated at the parcel-level or on the data resampled on subplots with 10 m resolution and these predictions were aggregated at the parcel-level. The analysis of the prediction consisted in the analysis of the root mean squre error (RMSE), the residual prediction deviation (RPD), the shape of the distribution of the predictions and of the residuals (equal to the actual value minus the predicted) and the over-/under-estimation of CSH available at the parcel level.

## Results and discussion

The RPD are quite similar to the one achieved before (Table 1).

Table 1. Residual prediction deviation (RPD) of validation of the four models applied at the parcel (RPD_Parcel) or at the subparcel level (RPD_SubParcel).

| model | RPD_Parcel | RPD_SubParcel |
|---|---|---|
| cubist | 0.79 | 0.81 |
| glmnet | 0.00 | 0.00 |
| nnet | 0.89 | 0.89 |
| rf | 0.94 | 0.93 |

The 0 RPD value for the glmnet model is due to a failure in predicting finite and believable value for some observations. Beside that, the RPD are similar to the one achieved in the study developing the models, the value of the residuals seems to increase with a rise of the original CSH, no matter which way the predictions were made (Figure 1). This effect is faint due to the low number of extreme values in the dataset. This, together with the distribution of the predicted values confirm the grouping effect of the prediction constated in the original study. It might be due to a higher percentage of values between 50 and 100 mm of CSH in the training datasets. Although predictions were grouped for all models, the predictions were different between the models (the correlation with the actual CSH for the cubist model was 0.20, for the glmnet -0.08, for the nnet 0.39 and for the rf 0.63).

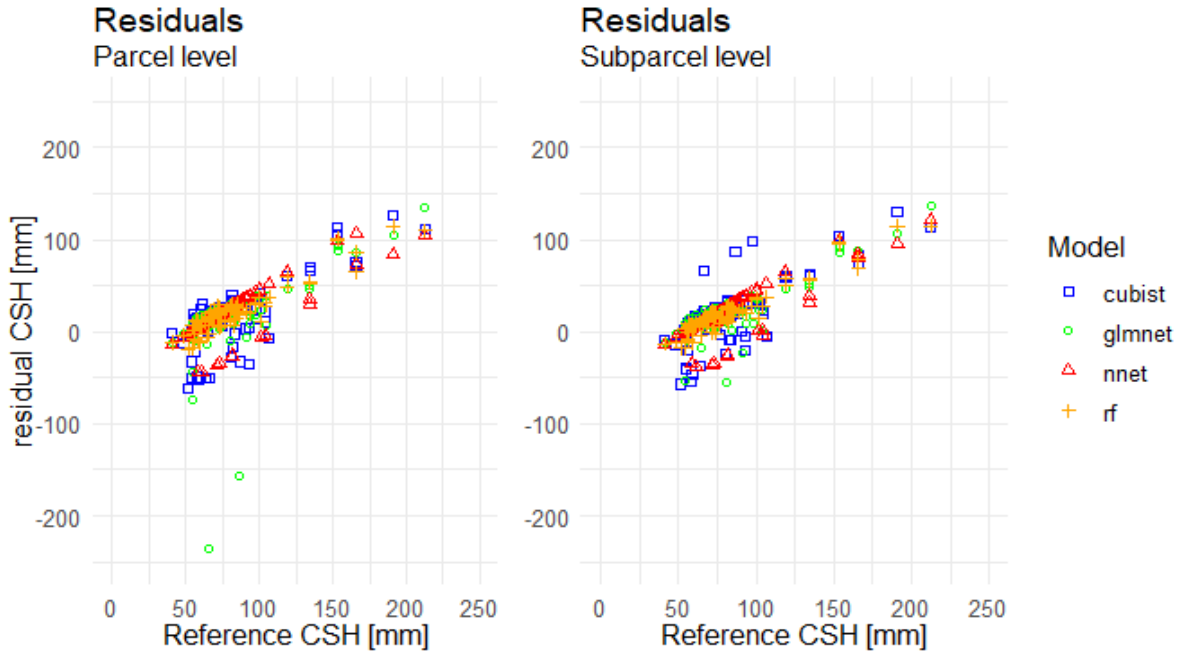


Figure 1. Representation of the residuals VS the original compressed sward height (CSH) dataset for both the validation made at the parcel (left) or at the subparcel level (right).

To obtain more correct predictions, we could change the training dataset with a more equal sampling or keep our current models and add a new ML layer that uses the predictions of the most promising models as input to predict the biomass at the parcel scale. The maximum correlation between the predictions of two models is between the cubist and the rf and is 0.73. This difference means that they read different parts of the signal and this validates the new ML layer approach. Another key argument is the value of the adjusted R-squared ($R^2$=0.49) for the linear regression predicting the actual CSH on the basis of the 4 model predictions. Moreover, it could help in training the final model with more datasets that were recorded without an accurate positioning system.

## Conclusion and outlook

The 4 models developed and selected previously to predict biomass did not show good performances once applied to data acquired at the parcel level with a different RPM used on a different validation farm. The difference in behaviour of the predictions and residuals indicates that there might be a way to improve the parcel-scale biomass estimation by adding a new ML layer which would be calibrated on paddock-scale data.

## Acknowledgements

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# Case study on monitoring sward height and available biomass with a rising plate meter on pastures of dairy farms in Southwest Germany

Werner J.[1], Stumpe C.[2], Höhn D.[1], Bateki C.[1] and Dickhöfer U.[1]

*[1] Institute of Agricultural Sciences in the Tropics, University of Hohenheim, Fruwirthstr. 31, DE-70599 Stuttgart, Germany; [2]Institute of Agricultural Engineering, University of Hohenheim, Garbenstr. 9, DE-70599 Stuttgart, Germany*

## Abstract

Pasture management on rural and extensive small-structured dairy farms in southwest Germany is based mainly on visual estimations or traditional management strategies. To maintain and optimize grassland management for pasture use, continuously measured data over the full vegetation period are crucial. However, the measurement of pasture characteristics can be time-consuming and challenging; therefore there is a considerable potential to use sensor-based technologies. In the present study, the potential of using a semi-automated rising plate meter to measure sward height data from pastures on four dairy farms in the Black Forest region was assessed. In addition, above-ground biomass based on grass cuts of pastures were compared to estimations of available biomass from the rising plate meter. The data revealed that pastures were overgrazed during late summer and autumn, with sward heights below 2 cm on three of four farms and the availability of pasture biomass decreased from 262 to 95 kg DM $ha^{-1}$ in autumn. The estimations from the rising plate meter constantly overestimated the available biomass on pasture, except for measurements in late summer. We conclude that the application potential of the rising plate meter at its current state might be limited and needs further adaptation for use with heterogenous short-grass swards.

**Keywords:** sward height, automated measurement, pasture management, Kurzrasenweide, organic milk production, grass-based nutrition

## Introduction

Pasture access is a central element in extensive small-structured organic dairy farms. Grazing is a substantial component of the diet of many organic dairy cows in the Black Forest region in the South of Germany. Various pasture management strategies are used in the region, with short-grass grazing being very prevalent. The short-grass grazing aims to keep the sward very short by adjusting stocking densities to forage growth rates, and thereby to enhance plant regrowth and maintain a high-quality sward (Häusler *et al.*, 2006). However, evaluation of forage availability on pastures in southwest Germany is usually based on visual assessments, which are subjective and challenging. Consequently, the development of automated sensors to estimate sward height has advanced towards applicable sensor systems. In the present study, the Grasshopper system, already validated and calibrated on temperate permanent grasslands (French *et al.*, 2015), was used on four commercial organic farms in southwest Germany to assess the sward height over a full vegetation period. Estimations of available biomass using the rising plate meter, based on calibrations for homogenous swards, were compared to above-ground biomass grass cuts of heterogenous pastures of permanent grasslands.

## Materials and methods

Data were collected during the vegetation period of 2020 on four commercial organic dairy farms in the Black Forest region around Titisee-Neustadt, Germany. The farms are located at 940 m a.s.l. on average. The pastures are permanent grassland dominated by perennial ryegrass (*Lolium perenne* L.) and white clover (*Trifolium repens* L.) with diverse herbs. The vegetation period was divided into five sub-periods (SP), namely, SP1 (May 29 – June 1), SP2 (June 27 – July 1), SP3 (July 27 – August 19), SP4 (September 9 – September 30), and SP5 (October 27 – October 28). During each SP, the above-ground biomass was harvested within a 0.5 m x 2 m rectangular quadrat placed randomly on the pastures. At each sampling point on the pastures, the sward within the quadrat was cut to about 1 cm above the ground using an electric grass cutter (Makita DUM604ZX, Germany) and the fresh weight recorded. The harvested material was then dried in a forced-air oven at 105°C for 16 h to estimate its dry matter content.

In addition, measurements of compressed sward height (CSH) were conducted using the Grasshopper system (TrueNorth Technology, Ireland). The system comprises a rising plate meter, which assesses the CSH when the plate falls freely onto the vegetation, and the height of the plate on the pole is recorded via ultrasonic measurements. Five measurement points were taken for each sampling point and the mean of all points per sample will be reported. Negative sward height values were removed. In total, *n* = 153 valid samples with sward height measurements and grass cuts were taken across the five periods and four farms. The grasshopper system uses the measured CSH to estimate the available biomass based on calibrations made for homogenous swards. In this study, the residual height and dry matter content within the calibration formula of the Grasshopper system was set to 1 cm and 25% dry matter content, respectively.

## Results and discussion

Comparing the mean CSH values of all farms in the outlined periods, there was always a higher CSH value for Farm 4 detected, in comparison to the other three farms. This could give an indication of a different or less efficient pasture management. The recommended sward height, which should be maintained within a short-grass grazing pasture management, is 4-6 cm compressed sward height (Häusler *et al.,* 2006). On the grazed pastures of the four farms, the targeted sward height was achieved during SP1 and during SP2 (Table 1). However, the CSH in the following periods might have been too low to maintain a high-quality pasture for grazing dairy cows, as a minimum of 3.5 cm as post-grazing sward height is recommended for pastures of dairy cows (Kennedy *et al.,* 2009). Frequent sward height measurements would thus offer the possibility to react faster to overstocking or understocking of pastures.

Table 1. Mean compressed sward height (CSH, mm) measured with the Grasshopper system, available biomass based on grass cuts (GC, kg DM $ha^{-1}$), estimated biomass with the Grasshopper system (GH, kg DM $ha^{-1}$) across all pastures of four farms in the Black Forest, Germany, in the vegetation period of 2020.

| Sampling period | Farm 1 | | | Farm 2 | | | Farm 3 | | | Farm 4 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CSH | GC | GH | CSH | GC | GH | CSH | GC | GH | CSH | GC | GH |
| 1 | 40.3 | 167 | 481 | 38.0 | 190 | 391 | 42.3 | 181 | 463 | 98.1 | 715 | 2467 |
| 2 | 38.4 | 340 | 370 | 37.1 | 85 | 381 | 34.7 | 47 | 304 | 79.8 | 388 | 1805 |
| 3 | 21.4 | 60 | 99 | 26.0 | 81 | 150 | NA | NA | NA | 66.7 | 443 | 1270 |
| 4 | 18.7 | 448 | 102 | 12.3 | 170 | 36 | 7.1 | 145 | 6 | 30.1 | 161 | 282 |
| 5 | 12.0 | 62 | 26 | 12.7 | 56 | 31 | NA | NA | NA | 34.2 | 156 | 337 |

With regards to the comparison of the estimated biomass by the Grasshopper system to the available biomass as based on the measured pasture cuts, there was an overestimation by the Grasshopper on all farms in all periods, except during SP4 and SP5 and for Farm 4 (Table 1). Towards the end of the vegetation period there is a decline in biomass and also in the compressed sward height. Therefore, this might display a limitation of the rising plate meter, as it is not reporting the actual biomass on very short-grass swards. On Farm 3, there were more invalid values for sward height towards the end of the vegetation period, with lower sward height reported. This may be linked to the low amount of biomass. Similar to studies of Murphy *et al.* (2020) and Hart *et al.* (2020), there might be a strong effect of the botanical composition of the pastures. This will be further analysed in future work.

## Conclusions

The results demonstrate the importance of a continuous measurement of the pasture vegetation to optimize pasture management as there is a high risk of overgrazing especially towards the end of the vegetation period. Automated measurement systems, such as the rising plate meter Grasshopper,

enables continuous monitoring and information-based adjustment of stocking densities and pasture access throughout the grazing season. However, at the moment there is still a limitation of the Grasshopper system in measuring available biomass accurately, especially if there is only a small amount of biomass available. Therefore, the calibrations need to be adapted to short-grass, heterogenous swards.

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# Influence of microplastics on the leaf temperatures of ryegrass

Cornelsen H. and Wrage-Mönnig N.

*Grassland and Forage Science, Faculty of Agricultural and Environmental Sciences, University of Rostock, Justus-von-Liebig-Weg 6, 18059 Rostock, Germany*

## Abstract

Production rates and global consumption of synthetic polymers have grown exponentially in recent years. Associated with environmental problems such as mismanaged plastic debris, inefficient water treatment plants or anthropogenic littering behaviour, this increase has resulted in a vast amount of all-size plastic entering the environment. Due to its subsequent resistance to degradation, plastics are persisting in the environment and can potentially influence environmental processes. Primarily microplastics (< 5 mm) are central to the debate. So far, aquatic systems have been in the focus of concern. Our knowledge on microplastics in terrestrial ecosystems, especially agricultural soils and crops, is very limited. Lab experiments have shown depression in germination of grassland plants, possibly due to changes in water availability. Therefore, the aim of this research was to investigate the influence of different sizes of microplastics simulated by Polyvinylchloride on the leaf surface temperatures of *Lolium perenne* in an outdoor pot experiment. The leaf temperature is a proxy for transpirational cooling and thus water availability. An infrared image of the plants was taken weekly, using a high definition thermographic camera. We partially observed higher leaf surface temperatures for plants with different-sized microplastics. The temperatures were significantly higher for plants without fertilizer treatment.

**Keywords:** microplastics, infrared imaging, leaf temperatures, transpirational cooling

## Introduction

Microplastics (MP) in terrestrial ecosystems have just recently started to gain societal and scientific interest, due to the ubiquity of MP that has been found worldwide. MP can enter soils via aeolian transport or rain (Bergmann et al., 2019) as well as by commonly used agronomic practices like use of plastic mulch films (Li et al., 2020) or application of sewage sludge and biowaste (Weithmann *et al.*, 2018). Recent studies have reported various effects of MP acting as a stressor for soil organisms and plants (Bosker *et al*., 2019; Huerta Lwanga *et al*., 2017). As microplastic research concerning the soil-plant system and plant development is just emerging, there is a lack in quantity and quality of comparable analytical methods (Qi *et al*., 2020). In previous experiments, we observed depressions in germination and general plant performance for plants exposed to MP. Beside this, enrichments in isotopic signatures ($\delta^{13}C$) were observed, indicating a potential disturbance in water balance of ryegrass. The focus of this experiment was therefore to study potential drought stress of plants caused by MP. We used thermographic measurements of leaf surface temperatures as a proxy of transpirational cooling and thus water availability. We hypothesized that MP would reduce water availability and thus increase plant leaf temperatures.

## Material and methods

We used perennial ryegrass (*Lolium perenne*) cv. Trivos (Deutsche Saatveredelung, Lippstadt, Germany) as a model species and Polyvinylchloride (PVC) to simulate MP in three different size ranges: powder: < 0.25 mm (Werthmetall, Erfurt, Germany); pellets: ~ 5 mm (Veka AG, Sendenhorst, Germany) and grist: ~ 7 -10 mm (Veka AG, Sendenhorst, Germany). An amount of 30 g was surface-applied per pot filled with 3 kg of local soil and approx. 250 seeds were sown at the end of June 2020. Fertilizer treatment (NPK-fertilizer) was an additional factor that was applied once (2 g) to half of the pots. We used 16 replicates per PVC and fertilizer treatment and additional control (n=8) containing only plastics and soil (N=136). Thermographic images of the plants were recorded weekly (n=5) in absence of direct sunlight, rain or wind using the high definition infrared camera VarioCam HD (Infratec GmbH, Dresden, Germany) starting seven weeks after sowing. For analysis, 25 temperature measurement points were manually set on the leaf surfaces of the plants. A mean temperature per pot was calculated from these

temperature points. Images were analysed using IRBIS Plus 3.1, Microsoft Excel and R Studio for graphics and ANOVA.

## Results and discussion

For most of the measurement dates, leaf surface temperatures were higher for treatments without fertilizer. At two dates of measurement, leaf surface temperatures were slightly higher for treatment with larger MP (macro) (Table 1).

Table 1. Leaf temperatures of perennial ryegrass measured with infrared thermography. Mean values and standard errors are shown for the single treatments (fertilized and unfertilized) with MPs (microplastics): control; macro (~ 7-10 mm); micro_a (< 0.25 mm); micro_b (~ 5 mm) for each date of measurement.

| Date | Control | | macro | | micro_a | | micro_b | |
|---|---|---|---|---|---|---|---|---|
| | fertilized | unfertilized | fertilized | unfertilized | fertilized | unfertilized | fertilized | unfertilized |
| 21.08.20 | 21.85 ± 0.32 | 22.40 ± 0.49 | 24.53 ± 0.28 | 25.08 ± 0.52 | 22.92 ± 0.37 | 22.92 ± 0.94 | 24.27 ± 0.29 | 24.88 ± 0.32 |
| 30.08.20 | 17.29 ± 1.03 | 17.82 ± 0.66 | 17.24 ± 1.15 | 17.50 ± 0.99 | 17.38 ± 1.09 | 17.72 ± 0.79 | 17.25 ± 1.00 | 17.72 ± 0.67 |
| 03.09.20 | 17.57 ± 0.43 | 18.07 ± 0.45 | 17.61 ± 0.50 | 18.16 ± 0.49 | 17.58 ± 0.44 | 18.11 ± 0.38 | 17.50 ± 0.45 | 18.14 ± 0.41 |
| 08.09.20 | 19.92 ± 0.72 | 19.99 ± 0.35 | 20.14 ± 0.69 | 19.95 ± 0.35 | 19.93 ± 0.75 | 19.93 ± 0.51 | 19.91 ± 0.82 | 20.18 ± 0.65 |
| 16.09.20 | 17.73 ± 0.32 | 17.98 ± 0.28 | 17.78 ± 0.33 | 19.93 ± 0.29 | 17.90 ± 0.44 | 18.00 ± 0.44 | 17.74 ± 0.34 | 17.97 ± 0.25 |

One date (3 September) of thermal imaging is shown graphically here; on that day, the images were taken at 5:30 PM with an average air temperature of 20°C. No significant effect of MP on the leaf surface temperatures of *Lolium perenne* was detectable for this date. However, leaf temperatures were significantly warmer in plants without fertilizer treatment (Figure 1).

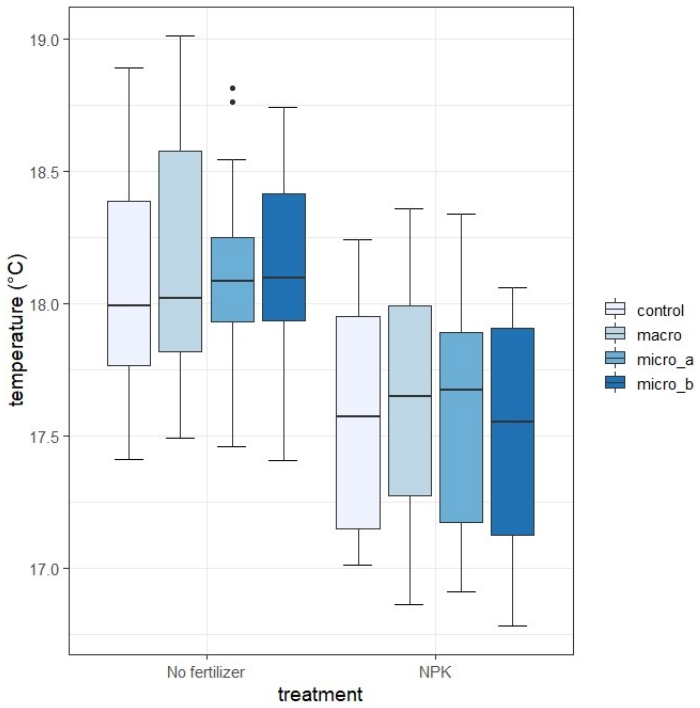


Figure 1. Mean values of leaf temperatures on 3 September 2020 (5:30 pm, 20°C air temperature) in °C presented in boxplots over the different groups of MPs (microplastics): control treatment, macro (~ 7-10 mm), micro_a (< 0.25 mm) and micro_b (~ 5 mm) for two fertilizer treatments (No fertilizer and NPK-fertilization).

This may be a result of reduced biomass in unfertilized plants, allowing the soil to emit more radiation detectable by the camera. As visible (Figure 1), leaf temperatures of plants exposed to MP were higher than the control treatment, but not in the group of fertilized plants with MP micro_b. Besides this, no clear effect of MP on leaf temperatures could be observed. As weather conditions were similar but rarely identical for dates of measurements, overall results were hard to compare. Therefore, an additional indoor experiment with younger plants of perennial ryegrass was conducted in autumn 2020 to minimize effects of the external circumstances. As we expect MP to have most influence during the initial stage of plant development, we hypothesize clearer results in younger plants. These results are currently being processed.

## Conclusions

No significant effect of MP differing in size could be observed for the selected date using infrared imaging. There was a trend towards higher temperatures for plants growing in soil with addition of MP. As our results may as well be partly a result of unsteady outdoor conditions, infrared imaging of plants may still be a promising procedure to more precisely understand the detailed effects of MP on plants.

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# The potential of unmanned aerial vehicle (UAV)-based multispectral data to estimate fresh grass allowance

Klootwijk C. W.[1], de Boer I. J. M.[2], van den Pol-van Dasselaar A.[3], Holshof G.[1], Fraval S.[4] and van Middelaar C. E.[2]

*[1]Wageningen Livestock Research, Wageningen University & Research, PO Box 338, 6700 AH Wageningen, the Netherlands; [2]Animal Production Systems group, Wageningen University & Research, PO Box 338, 6700 AH Wageningen, the Netherlands; [3]Aeres University of Applied Sciences, De Drieslag 4, 8251 JZ Dronten, the Netherlands; [4]Global Academy of Agriculture and Food Security, University of Edinburgh, Bush Farm Road, EH25 9RG Edinburgh, UK*

## Abstract

Accurate estimates of fresh grass allowance are central to improve the economic and environmental performance of pasture-based dairy farms. To accurately quantify fresh grass allowance, the total available herbage mass (HM) needs to be corrected for the occurrence of rejected patches (RP) that are formed due to selective grazing. The aim of this study was to explore whether multispectral images can be used to correct fresh grass allowance for selective grazing. To do so, we performed measurements in a grazing experiment. We used an unmanned aerial vehicle (UAV) mounted with a full colour and multispectral camera to record visible (red, green, blue) and near-infrared (NIR) wavelengths. We estimated HM using the Normalised Difference Vegetation Index (NDVI). We found a quadratic relationship between grass height (as a proxy for HM) and NDVI, which was influenced by date of measurement and grazing interval *($P<0.001$; RMSEP = 10.2%; $R^2 = 0.78$)*. We were able to identify RP by estimating threshold values in NDVI using visual interpretation of full colour images. Our results provide first indications that NDVI could be used to quantify fresh grass allowance for grazing. Further research will be required in order to develop a remote sensing method for accurate fresh grass allowance estimation under different grazing management practices.

**Keywords:** multispectral analysis, NDVI, herbage mass, grazing management, dairy cows

## Introduction

The economic and environmental sustainability of pasture-based dairy farms is largely driven by grassland utilization (Shalloo *et al*., 2018). To improve grassland utilisation it is necessary to accurately quantify fresh grass allowance. Fresh grass allowance is the amount of pasture offered to the cow in kg dry matter (DM) per cow per grazing day. To accurately calculate fresh grass allowance, we should correct total herbage mass (HM) for the occurrence of rejected patches (RP) that are formed due to selective grazing (Klootwijk *et al*., 2019).

The rapid advances in remote sensing technology create new opportunities for automated monitoring of HM, for example via multispectral images. Although widely adopted in arable production, the use of multispectral images is still in its infancy in grass-based dairy farming systems (Shalloo *et al*., 2018). The effect of grazing on the relationship between vegetation indices and HM is yet to be discovered (Moeckel *et al*., 2017). The aim of this study, therefore, was to explore whether multispectral images can be used to correct fresh grass allowance for selective grazing.

## Materials and methods

The grazing experiment was performed at the Dairy Campus research facility in Leeuwarden (NL) during the grazing season of 2017. Sixty dairy cows were allocated to two grazing systems, i.e. compartmented continuous grazing (CCG) and strip-grazing (SG), in duplicate. Both CCG and SG are rotational grazing systems in which the cows receive a new grazing area daily. These systems, however, largely differ in key grazing characteristics, such as pre- and post-grazing heights and period of regrowth (Klootwijk *et al*., 2019). In total we used 8 ha of grassland for day grazing with a fixed stocking rate of 7.5 cows $ha^{-1}$ of grazing area.

Grass height was quantified using a rising plate meter (RPM), where a W-shape was traversed in each compartment. The RPM is a non-invasive and internationally adopted method to quantify grass height

as a proxy for HM. Remotely sensed images were taken using an unmanned aerial vehicle (UAV) (eBee Ag) mounted with a full colour and multispectral camera (multiSPEC 4C) to record visible (red, green, blue) and near-infrared (NIR) wavelengths (flying height 120 m; image overlap 70%; ground sampling distance maximum 11.5 cm/px). These grass height recordings and remotely sensed images were taken on three days over the course of July and August. The remotely sensed images were used to calculate the Normalised Difference Vegetation Index (NDVI), using the red and NIR wavelengths. We used the zonal statistics software in the QGIS geo-algorithm toolbox (version 2.18.2) to calculate the average NDVI per field. The fields in the drone images were identified using latitude and longitude measurements of all field corner points taken with a Global Positioning Systems (GPS) device (Garmin GPSMAP 64S).

To understand the relationship between grass height measurements and NDVI recordings, we defined a regression model with grass height (averaged over the compartment) being the dependent variable, and NDVI, grazing interval, grazing system, measurement date, and fields being the explanatory variables. Since the literature shows a non-linear relationship between ground measurements of HM and multispectral reflectance (Hoving *et al*., 2018; Lussem *et al*., 2018), we introduced NDVI also as a quadratic term in the regression analysis. Using visual interpretation of full colour images, we set a minimum NDVI for RPs as a threshold value to create binary raster layers, categorizing RP and non-RP pixels for each field. First, we used these raster layers to calculate the percentage of grassland covered with RP. Subsequently, we used these raster layers to calculate the average NDVI of the non-RP, representing the fresh grass allowance per field.

## Results and discussion

Regression analysis showed that the quadratic relationship between grass height and NDVI is influenced by the date of measurement *($P < 0.001$)*. This is in line with the literature showing that the relationship between HM and NDVI is influenced by growing season (Hoving *et al*., 2018). In addition, we found an expected relationship between grazing interval (i.e., period of regrowth) and grass height *($P < 0.001$)*. The regression analysis resulted in a mean squared error of prediction (RMSEP) of 9 mm (10.2%) *($R^2 = 0.78$)*.

The yellow lines in Figure 1 represent the outline of compartments in which the green colour clearly represents RP. For CCG, NDVI values with RP ranged from 0.84 to 0.93, with an average of 0.89, whereas NDVI values without RP ranged from 0.82 to 0.92, with an average of 0.88. This reduction in average NDVI value of 0.01 seems rather small, but equals 11% of the range in NDVI with RP (0.09). For SG, NDVI with RP ranged from 0.67 to 0.90, with an average of 0.82, whereas NDVI without RP ranged from 0.67 to 0.90, with an average of 0.80. This reduction in average NDVI values also equals 11% of the range in NDVI with RP.


Figure 1. A full colour image of the different compartments in the grazing experiment.

The difference between NDVI with and without RP decreased with an increasing amount of days since grazing, which is expected since the detection of RP becomes more difficult when grass height of RP and non-RP increases.

## Conclusions

We showed the potential of a relatively easy method to correct fresh grass allowance for selective grazing based on multispectral images. Our results provide first indications that NDVI could be used to quantify fresh grass allowance for grazing, but further research will be required in order to develop a remote sensing method for accurate fresh grass allowance estimation under different grazing management practices, species composition and soil conditions.

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# Grass quality measurement with a handheld NIR sensor

Bussink D.W.[1], Sarjant S.[2], Thijssen D.[1] and Luleva M.[2]

*[1]Nutrient Management Institute, Nieuwe Kanaal 7C, 6709 PA Wageningen, the Netherlands; [2]Agrocares, Nieuwe Kanaal 7C, 6709 PA Wageningen, the Netherlands*

## Abstract

There is a need to determine grass quality during the grazing season to establish optimal rations in terms of CP content and to correct for low or high N fertilization. Recently, work has been done to determine grass quality using the NIR Handheld scanner of Agrocares. Grass samples from plots in the Netherlands and Germany were scanned in the lab, fresh and dried; 5 scans per sample. The dataset with dried samples was extended with scans of dry in-stock samples and another spectral database after spectral conversion. A calibration model was built for dried samples (n>6000). A subset of 337 fresh grass samples was used to make a conversion model between wet and dry samples. The validation models for CP of dry and fresh samples had RSME values of 22.7 and 25.8 g $kg^{-1}$ DM ($R^2$ = 0.68 & 0.58). Pilot use of the scanner on 10 farms took place in October 2019, measuring 5 spots directly in the field. These locations were then sampled and measured in a bucket. The results showed that CP was on average 6 and 2% lower compared to reference analysis, with a maximum deviation of 13 and 18% respectively. The results are encouraging to further expand the calibration database.

**Keywords:** grass, quality, scanning, crude protein, near infrared, handheld

## Introduction

Strict control of the protein supply to dairy cattle is necessary to limit the N excretion in manure and urine and thus the risk of N losses. Efficient feeding is particularly successful in systems where dairy cattle stay year-round in the barn. However, in the Netherlands, more than 80% of the dairy farmers apply grazing during the summer season. Optimization of protein in the ration is difficult because protein content in grass is poorly known and can vary greatly during the season depending on fertilization and yield. There is an urgent need for tools that predict/measure N content of grass. Worldwide, much work has been done with modelling and remote sensing techniques (Honkavaara *et al.*, 2020) but the applicability for grassland management support is still limited. Another route is direct non-invasive measurements. Agrocares has developed a Handheld NIR scanner (1300-2525 nm defined by the sensor specifications) for measuring soil and feed quality that is operated via a smartphone (Figure 1, www.agrocares.com). The goal is to make this sensor applicable for measuring grass quality directly in the field, to better control the (protein) supplementary feeding of dairy cattle and to use the information as a feedback for N fertilization. In this article we will elaborate on the realization of reliable grass quality predictions with the Handheld scanner.

## Material and Methods

To use the scanner a calibration model and handling protocol for field use must be developed. For the latter it was important to test how to place the scanner on the grass so that enough grass material is present under the scanning window with no interference of the soil below. Therefore, in the lab different layers of thickness of grass were placed on a plastic base with its own unique spectral signal. At a certain thickness of material, the spectral signal of the plastic will not be observed. As gathering calibration data is expensive and measuring fresh grass with a high water content (80-90%) is difficult, we therefore used a step-by-step approach by developing calibration models for dried samples (validation), followed by building a wet-dry conversion model. For the dried (milled) grass samples, we used in-stock samples primarily from the Netherlands and Germany gathered in 2016-18. These were analysed and scanned with the Handheld scanner (about 1600 samples), 5 scans per sample. In addition, we extended this spectral database with grass spectra from an older lab NIR sensor after spectral conversion to the Handheld spectra. In this way we obtained an additional 5000 spectra for different parameters to build a calibration model. A wet-dry conversion model was also built on 337 of the samples gathered in the Netherlands and Germany during 2018 so that incoming field samples could utilize this calibration model. The dry-sample calibration models are built with Locally Weighted Learning (Atkeson *et al.*, 1997) wrapped around a Gaussian Processes regressor (Rasmussen *et al.*, 2006).

Important wavelengths are identified by the model. The machine learning approach that we used does not yield these automatically. The wet-dry conversion model uses an ensemble of GP regressors to convert the spectra from wet to dry. The models were evaluated both with 10-fold cross-validation, and with an independent validation set of 49 samples, both in dry and wet (the conversion model is applied before prediction) states. In autumn 2019, a pilot field test on 10 practical farms took place using direct in-field measurements with the scanner. The grass was cut from the scanned spots, placed in a bucket, and scanned (5 times), and compared with regular lab analysis of the samples.

## Results

Experiments in laboratory conditions showed that 2 or more layers of leaves eliminate the spectral influence caused by the plastic. This means that grass at a grazing stage, and also a turf grass sward, should give enough layer thickness when the scanner is placed on top of the grass sward and stands by itself. This was confirmed in field testing. Due to the spectral difference between leaf tops and stems (different contents), and different grass composition between scanning spots, a first estimate based on at least 5 scans is necessary. However, this needs further evaluation and it also depends on the quality of the calibration.

The 10-fold cross validation results of dried samples for ash, fibre, protein, and sugar content showed $R^2 > 0.9$ (Table 1) with RMSE values varying between 10.5 and15 g $kg^{-1}$ DM.

Table 1. Calibration and validation results of dried grass samples and validation results of fresh grass samples (wet-dry).

| Element | Calibration dried samples | | | | | | Validation dry | | | wet-dry | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| (g $kg^{-1}$ DM) | n | 25% | median | 75% | RMSE | $R^2$ | n | RMSE | $R^2$ | RMSE | $R^2$ |
| Ash | 6722 | 52 | 98 | 120 | 12.17 | 0.91 | 49 | 12.12 | 0.53 | 14.56 | 0.31 |
| Fat | 2741 | 26 | 32 | 39 | 4.62 | 0.82 | 49 | 8.62 | -1.00** | 7.15 | -0.38** |
| Fibre | 6357 | 190 | 230 | 260 | 15.28 | 0.95 | 49 | 17.77 | 0.52 | 19.38 | 0.43 |
| $H_20$* | 6558 | 47 | 59 | 72 | 4.54 | 0.94 | 49 | 7.44 | 0.61 | 10.53 | 0.21 |
| Crude protein | 6948 | 88 | 160 | 210 | 10.45 | 0.98 | 49 | 22.68 | 0.68 | 25.82 | 0.58 |
| Sugar | 3971 | 8.1 | 41 | 88 | 12.18 | 0.95 | 49 | 20.35 | 0.64 | 28.96 | 0.27 |
| Sulfur | 238 | 2.2 | 2.8 | 3.8 | 0.51 | 0.84 | 48 | 1 | -1.53** | 0.96 | -1.32** |

* Amount of $H_2O$ when drying 70 °C dried samples to 105 °C. ** Model performs worse than predicting the mean.

Results on the validation set showed a drop to about 0.65 $R^2$ for sugar, protein, and fibre (Figure 1a, CP). The conversion to a model for wet samples (fresh grass) and the resulting validation showed a further decrease in $R^2$ (between 0.27 and 0.58), resulting in RMSEs for fibre, protein, and sugar of 19, 26 and 29 g $kg^{-1}$ DM respectively.

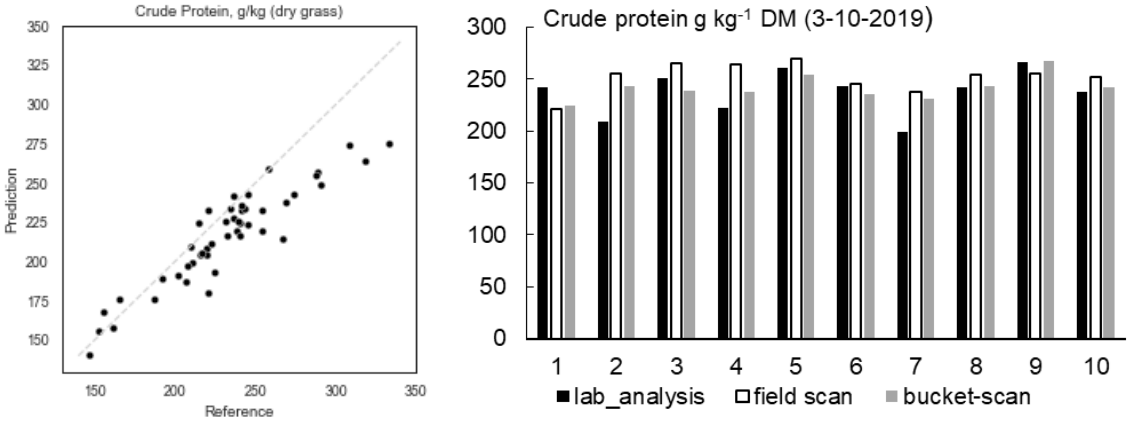


Figure 1. a) Validation results (dry) of crude protein ($R^2$=0.68) (left) and b) The crude protein content of 10 grass fields on 3 October 2019 measured with the Handheld scanner (right) on 5 spots, directly in the field and after gathering grass in a bucket.

This means that the calibration set is still not fully representative for Dutch grass. Grass samples of different years, different spots and from early to late season needed to build a more representative database. Also, the number of wet samples (fresh grass) was very limited and needs to be extended. On the other hand, future improvements are still possible with alternative machine learning algorithms and modifications to the scanner, such as increasing the scanning area. Further investigation is needed to determine why the validation results are quite poor (limited database and/or weak spectral signal).

The calibration model of Table 1 was used in the practical test, which was focused on crude protein. The lab-analyses, field scan (5 spots), and bucket scanning resulted in average CP contents of 237, 252 and 242 g $kg^{-1}$ DM. This suggests that bucket scanning (also five spots) is more accurate in predicting grass contents than spot scanning. Although further improvement of the predictions is necessary, the farmers showed great interest in the results and indicated that it could help them in their feeding and fertilizer management.

## Conclusions

The tested handheld scanner showed very good calibration results on dried samples. The prediction results of dry and wet validation samples were less good. This indicates a need for more attention to building a representative database. Bucket scanning of gathered samples from different spots seems the preferred way of using the scanner in field measurements.

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# Theme 2. Biodiversity and other ecosystem services

# Remotely sensed insights into grassland biodiversity

Rocchini D.

*Alma Mater Studiorum University of Bologna, Department of Biological, Geological and Environmental Sciences, BIOME Lab, via Irnerio 42, 40126, Bologna, Italy; Czech University of Life Sciences Prague, Faculty of Environmental Sciences, Department of Spatial Sciences, Kamýcká 129, Praha - Suchdol, 16500, Czech Republic*

## Abstract

Given the difficulties associated with field-based data collection, the use of remote sensing for estimating environmental heterogeneity is a powerful tool since it provides a synoptic view of an area with a high temporal resolution. This paper presents, as an example, a case study applied to a grassland area and provides insights about the potential use of remotely sensed data for estimation of grassland diversity.

**Keywords:** biodiversity, ecological informatics, heterogeneity, open source algorithms, remote sensing

## Introduction: biodiversity from above

Finding ecological proxies of species diversity is important for developing effective management strategies and conservation plans for natural areas at various spatial scales, whether local (e.g. Osborne *et al*., 2007), regional (e.g. Wohlgemuth *et al*., 2008) or global (e.g. Rahbek *et al*., 2007). Species information has traditionally been collected directly from the field prior to biodiversity assessment.

Inevitably, when sampling species in the field a number of issues need to be solved first, such as: (i) the number of sampling units to be investigated, (ii) the choice of the sampling design, (iii) the need to clearly define the statistical population, (iv) the need for an operational definition of a species community, etc. (Chiarucci, 2007). Furthermore, standardized field sampling or ground surveys, whether of plant or animal communities, are time-consuming and costly, despite being the most accurate methods for collecting species diversity data. Therefore, *a priori* knowledge of areas with higher diversity means that attention can be focused on them, thus helping to minimize the cost and time involved in monitoring (e.g. Rocchini *et al*., 2005).

The causal relationship between species diversity and environmental heterogeneity has been a long-lasting interest among ecologists. Environmental heterogeneity is considered to be one of the main factors associated with a high degree of biological diversity given that areas with higher environmental heterogeneity can host more species due to the greater number of available niches within them (Gaston, 2000; Hortal, 2008). Given the difficulties associated with field-based data collection, the use of remote sensing for estimating environmental heterogeneity and hence species diversity is a powerful tool since it provides a synoptic view of an area with a high temporal resolution (Loarie *et al*., 2007). For example, the availability of satellite-derived data, such as those gathered by the Landsat program, makes it feasible to study all parts of the globe with a resolution of up to 30 m (readers are referred to Tucker *et al*., 2004 for a description of the Global Land Cover Facility freely hosting this kind of data). In addition, Open Source systems for robustly analysing remotely sensed imagery are now also available (Rocchini and Neteler, 2012). From this point of view, the development of Free and Open Source algorithms to measure and monitor (i.e. repeated measures over time) landscape or ecosystem heterogeneity from space would allow robust, reproducible and standardized estimates of ecosystem functioning and services (Rocchini and Neteler, 2012). Furthermore, their intrinsic transparency, community-vetoing options, sharing, and rapid availability are also valuable additions and reasons to move towards open source options. Among the different open source software options, the R software is certainly one of the most used statistical and computational environments worldwide and different packages have already been devoted to remote sensing data processing for: (i) raster data management (raster package, Hijmans and van Etten (2020)); (ii) remote sensing data analysis (RStoolbox package, Leutner *et al*. (2019)); (iii) spectral species diversity (biodivMapR package, Féret and de Boissieu (2020)); (iv) Sparse Generalized Dissimilarity Modelling based on remote sensing data (sgdm package, Leitao *et al.* (2017)); (v) entropy-based local spatial association (ELSA package, Naimi *et al*. (2019)); or (vi) landscape metrics calculation (landscapemetrics package, Hesselbarth *et al*. (2019)), to name just a few, (vi)

diversity metrics on remote sensing data (rasterdiv package, Marcantonio *et al*. (2021)). Readers can also refer to https://cran.r-project.org/web/views/Spatial.html for the CRAN Task View on analysis of spatial data.

Spatial variability in the remotely sensed signal, hereafter referred to as spectral heterogeneity or spectral variability, is expected to be related to environmental heterogeneity and could therefore be used as a powerful proxy of species diversity. This is true in light of the Spectral Variation Hypothesis, which states that the greater the habitat heterogeneity, the greater the species diversity within it (Palmer *et al*., 2000, 2002), regardless of the taxonomic group under consideration. Besides random dispersal of species (Hubbel, 2001), a higher heterogeneity of habitats will host a higher number of species each occupying a particular niche (niche difference model, Nekola and White, 1999). This hypothesis has been successfully tested with various taxa, such as vascular plants (e.g. Gould, 2000; Foody and Cutler, 2006; Levin *et al*., 2007), lichens (Waser *et al*., 2004), ants (Lassau *et al*., 2005), birds (St-Louis *et al*., 2009), and mammals (Oindo and Skidmore, 2002).

## Grassland ecological patterns monitored by remote sensing

From a European perspective on nature conservation, cultural landscapes, including semi-natural grasslands, contain a mosaic of significant wildlife habitats (Moreira *et al*., 2006). The abandonment of traditional management techniques in favour of intensification of agriculture is quickly reducing the amount of traditional cultural landscape units within the landscape matrix, producing an overall homogenization of the landscape (Antrop, 2005). The loss of the traditional state of dynamic equilibrium between human intervention and natural dynamics, accompanied by the regeneration of natural systems (e.g. shrub encroachment), has direct implications on biodiversity (Rocchini *et al*., 2006).

As remote sensing is increasingly being incorporated into ecological management to support decision making, the need for rapid mapping of biodiversity is increasing continuously. As an example, grassland diversity can be estimated based on the previously mentioned relationship between heterogeneity and species diversity in the field (Spectral Variation Hypothesis).

Based on the aforementioned algorithms, grasslands areas have been extensively explored to measure diversity- or biomass-related patterns directly from remotely sensed imagery. As an example, Vescovo and Gianelle (2006) demonstrated the power of the ASPIS (Advanced Spectroscopic Imaging System) for measuring the green herbage ratio (GR), the equivalent of the biomass/(biomass + necromass), i.e. an important biophysical parameter as it is a fundamental indicator of photosynthetic activity of vegetation components, with an $R^2$ overwhelming 0.70.

Biomass-related measurements are quite simple to attain by remote sensing data. This is also true for the well-established measurement of phenological variability. Reed *et al*. (1994) made use of the Normalized difference vegetation index (NDVI) data derived from the National Oceanic and Atmospheric Administration's Advanced Very High Resolution Radiometer (AVHRR) satellite sensor to measure key phenological events in different ecosystems including grasslands. They achieved a strong coincidence between the satellite-derived metrics and predicted phenological characteristics, e.g. the interannual variability of spring wheat in North Dakota, characterized the phenology of four types of grasslands.

In contrast to the measurement of many other vegetation attributes, plant species composition is difficult to detect with remote sensing techniques (Schmidtlein and Sassin, 2004).

The mapping of continuous floristic gradients might also be affordable when relying on hyperspectral imagery, namely a remote sensor with several spectral bands, in each of which there might be peaks of reflectance for different species. This would be particularly useful in grassland ecosystems in which different herbs and annual species might show a very similar reflectance pattern when relying on few bands or, in the worst case, on only the visible part of the spectrum (i.e. the part that the human eye is able to see, from the blue to the red wavelengths). A practical example is provided by Schmidtlein and Sassin (2004). These authors spatially modelled floristic gradients in Bavarian meadows by extrapolating axes of an unconstrained ordination of species data. This allowed them to map floristic gradients based on high-resolution hyperspectral airborne imagery, with a high agreement with ground-based data, up to an $R^2$ equalling 0.71. From this point of view, satellite remote sensing has been widely used for grassland diversity estimate, including the use of: (i) low resolution AVHRR data for studying

wide grasslands biodiversity (Oindo and Skidmore, 2002), (ii) multitemporal data for grassland diversity dynamics investigation (Alì *et al*., 2026), (iii) Sentinel-1 and Sentinel-2 data for the prediction of plant diversity (Fauvel *et al*., 2020).

Remote sensing is clearly not a panacea for solving measures and issues concerned with all organism-based aspects of diversity, like taxonomic, functional, genetic; but it can represent an important exploratory tool to detect diversity hotspots and their changes in space and time at the ecosystem level. In this *Proceedings* paper, I hope to stimulate debate about the power of remote sensing for investigating grassland diversity.

The symposium presentation of this paper shows additional examples including unmanned aerial vehicles (e.g., drones) which are expected to provide good results for present and future research in this field, given the generally high spatial resolution of images as well as the possibility to customize camera settings, and make use of different wavelengths-based sensors depending on the final ecological aims.

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# Grassland vegetation monitoring: scale is important

Marcinkowska-Ochtyra A.[1] and Kupková L.[2]

*[1] Department of Geoinformatics, Cartography and Remote Sensing, Chair of Geomatics and Information Systems, Faculty of Geography and Regional Studies, University of Warsaw, 00-927 Warsaw, Poland; [2] Department of Applied Geoinformatics and Cartography, Faculty of Science, Charles University in Prague, Albertov 6, 128 00 Praha 2, Czechia*

## Abstract

This paper gives a broad perspective on the key aspects of grasslands monitoring, with a focus on scale of analysis. The section 'Monitoring of grasslands using remote sensing: key aspects' discusses interrelated aspects important in grasslands mapping. The section 'Classified vegetation unit' is devoted to a brief description of classifiable units, such as species, communities/habitats or ecosystem types. Next, Unmanned Aerial Vehicles (UAVs), and aerial and satellite platforms are presented, followed by a discussion of data resolution within the context of mapping. The 'Methods of the data collection, processing and analysis' section encompasses field data collection, additional variables and classification algorithms. Each section provides examples of grassland mapping studies. Recommendations for practitioners from these studies are highlighted in the 'Conclusions' section.

**Keywords:** communities, ecosystem types, habitats, mapping, scale, species

## Introduction

Grasslands are one of the most challenging study objects of research due to their spatio-temporal dynamics. Remote sensing can provide biophysical parameters and also classify species, communities/habitats or ecosystem types. Focussing on classification is encouraged when it brings a reasonable cost reduction in comparison to field research, and when the data provide the required level of information and scale (Bock *et al.*, 2005). During the last 30 years there has been significant technological development of consistent, accurate and robust tools for grasslands mapping (Ali *et al.*, 2016).

In the mapping context, different scales play a role: the scale of time, and the scale of spectral and spatial data resolution have to be considered. Firstly, an important aspect is the vegetation **unit** as the study object. It is selected depending on what the final map will be used for: do we want to focus on individual species in a specific place, or are we interested in a general but more spatial overview of grassland communities? Different physiognomies of species in different growing stages can be captured by remote-sensing instruments, depending on the data **resolution** and date of acquisition. In this context, special attention should be paid to the **spatial**, **spectral** and **temporal resolutions** of acquired data; however, as is well known, they vary for different **platforms – satellite**, **aerial** or **UAV**. For monitoring practice it is important to achieve a high accuracy of mapped unit classification. Hence, beside the aforementioned aspects, the **methods** of data processing and analysis play a crucial role.

The goal of this study is to give an overview of the key aspects of grasslands mapping using optical remote sensing based on our relevant experience and studies in north-eastern Europe, and taking into account scale of analysis. We aim to evaluate these aspects in terms of the potential to maximize classification accuracy. Classification accuracy is assessed by User's Accuracy [UA] and Producer's Accuracy [PA] for classified categories/objects, and by Overall Accuracy [OA] and Kappa for all classified images. (PA is the probability that a reference class is classified correctly, UA is the probability that a pixel in the classification actually represents this reference (field) class; OA is defined as a share of correctly classified pixels on the total number of pixels and Kappa index compares the result of the classification with the classification created by a random process of classifying pixels into individual classes (1 means a perfect match and 0 represents a purely random result; Jensen, 2005)).

All above mentioned scales/aspects are interconnected and their evaluation should lead to a better understanding of how remote sensing can improve grasslands monitoring practice.

## Monitoring of grasslands using remote sensing: key aspects

In this section we discuss key aspects of grasslands monitoring using remote sensing in terms of the scales mentioned in the Introduction. They all influence the final map (Figure 1).

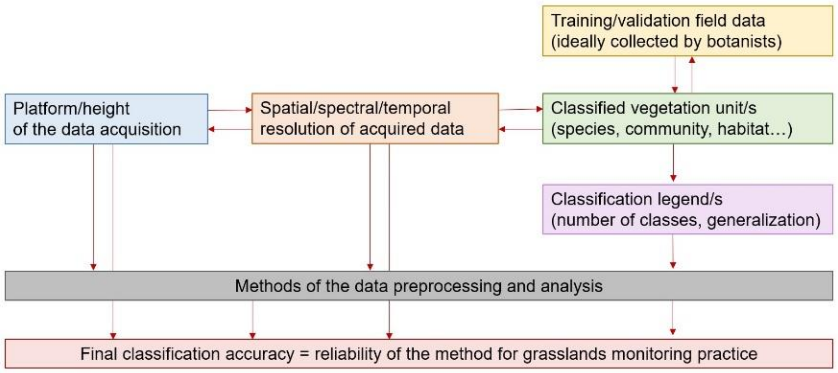


Figure 1. Key aspects of grassland monitoring using remote sensing.

### *Classified vegetation unit*

The minimal mapping unit is usually set according to the goals of the grasslands monitoring and is dependent on the features of available remote-sensing data. Traditionally, vegetation units are delimited based on expert phytosociological knowledge. Since we are analysing grasslands with the use of remote sensing, we expect that different units may be 'visible' from the sensor. Based on common literature in which grasslands have been classified with remote-sensing data, we can distinguish single species or larger complexes that form communities or habitats, or, ultimately, we may be interested in a grassland ecosystem as a whole. Selecting the appropriate unit that can be classified with specific data allows us to determine the optimal legend of the final map. Classifications of grasslands in relict Arctic–alpine tundra of the Krkonoše Mts (Czechia) at the level of habitats and communities (closed alpine grasslands dominated by *Nardus stricta*, grasses except *Nardus stricta* and subalpine *vaccinium* vegetation) were performed by Suchá *et al.* (2016) and Kupková *et al.* (2017) on satellite remote-sensing data (Landsat 8 and Sentinel-2). The same studies provided satisfactory results on the level of selected individual dominant grass species classified from aerial hyperspectral (HS) and multispectral (MS) data. For example, *Nardus stricta* stands were classified with 79% PA and 87% UA from aerial HS data. In the case of *Deschampsia caespitosa*, stands PA reached 88% and 89% UA using the same data.

### *Platform (height) of data acquisition*

Scale of mapping and related spatial resolution are described in more detail in subsection 2.3 and depend on the platform used (height of the data acquisition; Table 1).

Table 1. Main features of remote-sensing platforms.

| Platform | Satellite | Aerial | UAV |
|---|---|---|---|
| **Height above ground** | Hundreds of kilometres | Hundreds of metres to several kilometres | Tens to hundreds of metres |
| **Area size** | Up to global/continental level | Regions (square kilometres) | Localities (hectares) |
| **Spatial res.** | Hundreds of metres to metres | Metres to tens of centimetres | Tens of centimetres to centimetres |
| **Costs** | Some freely available; commercial expensive | Rather high | Relatively cheap, cheaper than aerial and commercial satellites |
| **Main advantages** | Regular overflights; coverage of extensive area | Big area with high spatial res.; different sensors at one time | Operability (temporal, spatial res.); use of different types of sensors |
| **Main weaknesses** | Clouds; rather low spatial res. | Clouds; permission; costly | Clouds; wind; permission; small area |

*Data resolutions*

The final scale of elaboration and classification accuracy of grasslands depends on spatial, spectral and temporal resolutions, which are based on data acquisition platform and sensor.

**Spatial resolution**

Spatial resolution is the main parameter influencing classification detail (the number of legend categories that are distiguishable). To be able to determine the best scale of elaboration, studies that tested different spatial resolutions within the same area and used classificaton legends with different number of categories are important. When we compared data with different spatial resolutions classified for the same area in the Krkonoše Mts, all 8 categories (six grass species and two other vegetation categories) were distinguishable from UAV HS and MS data (see Figure 2 – results for UAV data). While the legend had to be generalized for satellite and aerial data it was not possible to distinguish some less abundant grass categories and individual trees/shrubs in their pixels.

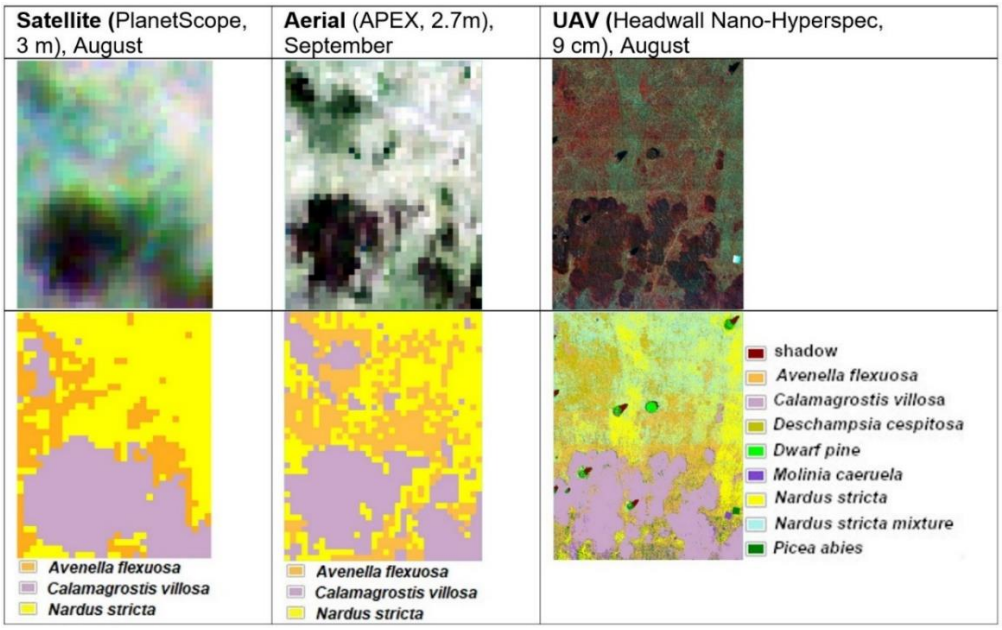


Figure 2. Data and classification results (research plot Zahrádka; Kupková *et al.*, 2021).

The other aspect is classification accuracy in case of different number of classified categories. Figure 3 compares obtained classification accuracies in case of legends with 8, 5 and 3 categories. When pixel size reached centimetres (HS UAV data), and also metres (PS data), it was possible to classify dominant *Calamagrostis villosa* and *Nardus stricta* species with reasonably high accuracies (Figure 3).

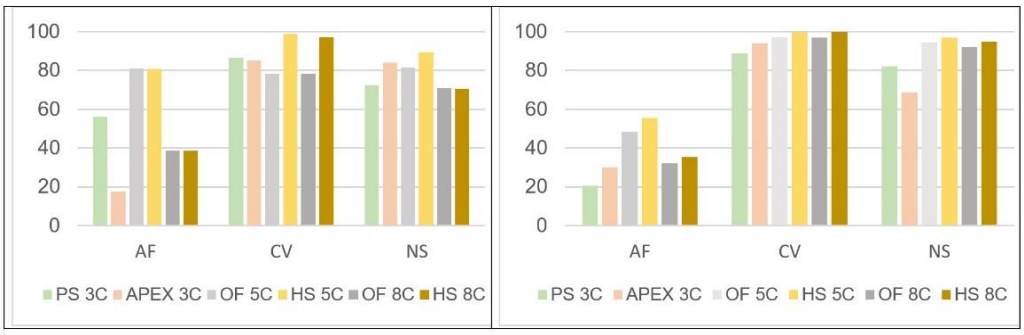


Figure 3. Best achieved results of PA (left) and UA (right) in % for selected grass categories (Kupková *et al.*, 2021). AV – *Avenella flexuosa*; CV – *Calamagrostis villosa*; NS – *Nardus stricta*; PS 3C – PlanetScope data, legend with 3 categories; APEX 3C – APEX data, legend with 3 categories; OF 5C – UAV RGB orthophoto, legend with 5 categories; HS 5C – UAV HS data, legend with 5 categories; OF 8C – UAV RGB orthophoto, legend with 8 categories; HS 8C – UAV HS data, legend with 8 categories).

Moreover, the number of classified categories did not play a significant role in final accuracy (see the accuracy of *Calamagrostis villosa* and *Nardus stricta* for HS UAV data or ortophoto using legend with 5 and 8 categories). Meanwhile, for species with low coverage (*Avenella fleuxosa*), even data with extremely high spatial (and spectral) resolution need not provide sufficient accuracy (UA around 50% for HS UAV data with 9 cm pixel). And it seems that higher number of categories leads in this case to a lower classification accuracy (compare UAs and PAs of *Avenella fleuxosa* for orthophoto and HS UAV data using legend with 5 and 8 categories). Smaller pixel size does not always bring better accuracy, the species coverage/abundance and a number of classified categories also plays a role.

In such a situation, it would appear to be of value to analyse data with the same spectral resolution but different spatial resolution. When vegetation of the Karkonosze Mts in Poland was classified on spectrally similar APEX (Airborne Prism Experiment) and EnMAP (Environmental Mapping and Analysis Program) data at very different spatial resolutions of 2.7 m and 30 m, respectively, the results for grasslands were both still highly satisfactory (for APEX about 98% UA and PA and for EnMAP 94% PA and 86% UA; Marcinkowska-Ochtyra *et al.*, 2017). However, due to the large EnMAP pixel, it was not possible to distinguish two classes (herbs and ruderal vegetation), so the final legend was developed just for this data. Nevertheless, among the eight classes, grasslands came second in terms of accuracy.

As mentioned above, an important feature is the coverage of the vegetation unit in the polygon used for classifier training. In the research where 1-m HySpex data were used for species classification in the Jaworzno Meadows Natura 2000 area in Poland, homogeneous patches of *Molinia caerulea* species with rare coexistence with other species were determined with high accuracy (more than 80%), while for *Calamagrostis epigejos*, often co-occurring with *Solidago* spp., it was difficult (about 60% PA and UA; Marcinkowska-Ochtyra *et al.*, 2018a). Empirical studies have revealed that less than 40% coverage of species results in lower accuracy.

**Spectral resolution**

The differentiation between particular species/habitat/communities in available spectral ranges allows them to be classified properly. The significance of spectral resolution as compared to spatial resolution, and their synergy, is discussed in vegetation mapping studies. In Suchá *et al.* (2016), orthoimages of 12.5-cm pixel and four bands performed better than WorldView-2 satellite data with better spectral resolution (eight bands) and lower spatial resolution (2 m), so spatial resolution proved to be more significant (in both cases, bands were registered in visible and near infrared [VNIR] range). However, UAV MS data with 1-cm pixel (orthophoto) were classified with significantly lower accuracy than UAV HS data with 9-cm pixel (OA differ by about 10 percentage points for eight and five legend categories [Kupková *et al*., 2021]).

A breakthrough in remote sensing is planned to be provided in 2022 by HS satellites as part of the aforementioned EnMAP mission, and these will include up to 99 bands from VNIR and up to 163 bands from SWIR (shortwave infrared) regions. High grasslands classification accuracy was obtained by this high spectral resolution of simulated data (as the pixel is only 30 m; Marcinkowska-Ochtyra *et al.*, 2017). However, currently available MS Sentinel-2 data also has valuable bands that are fewer in number (13) but that are relevant to vegetation analysis – two SWIR and red-edge bands, which have been shown as the most important in grasslands classification of the Karkonosze Mts (PA and UA more than 70% [Wakulińska and Marcinkowska-Ochtyra, 2020]).

**Temporal resolution**

As the physiognomy of grasslands is dynamic in time and affected by, for example, weather or management practice, the most important date during the growing season should be indicated for a given species or community/habitat. This specific timing is important because it allows grasslands to be distinguished from background based on knowledge of the specific phenological development of particular classes. For example, the best time for species identification was September for *Calamagrostis epigejos*, as this was the time of optimum fruit formation, and August for *Molinia caerulea*, when it was in flower (Marcinkowska-Ochtyra *et al.*, 2018a). However, that last date of data acquisition was the beginning of September and *Molinia* were not yet changing colour, as Schuster *et al.* (2015) recommend. So the results could be better if data from near to the end of September were used.

Multi-temporal classification, which takes into account datasets consisting of several terms of data acquisition, can be viable when spectral information is insufficient to distinguish similar grasslands. Multi-temporal orthophotos and HS data provided better results than did single-date data (1–3% difference in favour of multitemporal composites from two terms; Kupková *et al.*, 2021). When analysing three grassland Natura 2000 habitats at the Ostoja Nidziańska site in Poland (6210 – semi-natural dry grasslands and scrubland facies, 6410 – *Molinia* meadows and 6510 – lowland hay meadows) HySpex combined data from May, July and September also allowed higher accuracy than single-date data (Marcinkowska-Ochtyra *et al.,* 2019). However, July and September datasets provided comparable results (the differences in PA and UA less than 2%). It is worth emphasizing that there are not many studies that use multi-temporal HS data on grasslands. At the moment they are rather expensive, and the use of satellite data such as Sentinel-2 in this context is valuable. Wakulińska and Marcinkowska-Ochtyra (2020) proved that combining the first three out of four analysed terms (31 May, 7 and 27 August, and 18 September) provided the best OA (about 80%; 70–72% for single-date) and, of the eight analysed vegetation classes, the greatest significance was for grasslands. The aspect of high temporal resolution allow denser time series to be used that can lead to even more detailed analysis.

## *Methods of the data collection, processing and analysis*

### Field data collection

Reliable grassland classification is also subject to the availability of accurate training and validation field data. It is important that they are synchronous with image data collection and fit the data resolution and vegetation unit. Collaboration between specialists in geoinformatics and botanists is essential to obtain high accuracy. The map legend is defined based on vegetation unit and presented classes (all classes occurring in a given area or only the objects of interest, e.g. grassland species). It is valuable to observe their additional features (coverage, dry matter, dominant/coexisting species, etc.).

### Additional variables

Apart from using the spectral bands themselves, the use of additional variables like spectral indices, Airborne Laser Scanning (ALS) derivatives, transformation products or additional terms of data acquisition can potentially raise final grasslands classification accuracy (Bock *et al.*, 2005). Some species prefer specific habitats (e.g. wet for *Molinia caerulea*), so adding topographic indices to the classification can increase accuracy. However, this is not valid for the wider ecological spectrum of *Calamagrostis epigejos* (Figure 4).

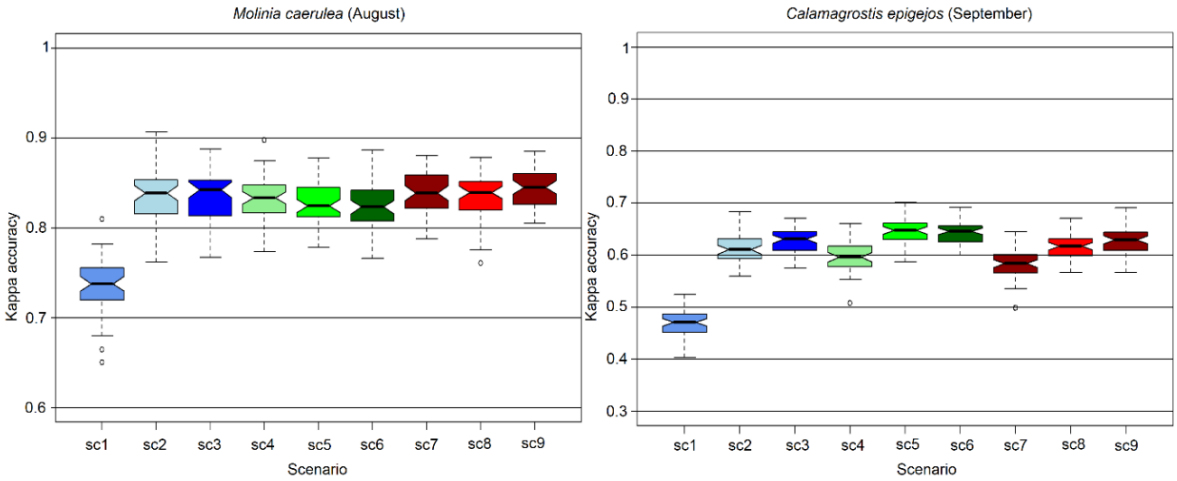


Figure 4. Kappa accuracies for different scenarios of datasets for expansive species mapping (sc1 – original bands, sc2 – Minimum Noise Fraction (MNF) transformed bands, sc3 – MNF+Canopy Height Model, sc4 – MNF+vegetation indices, sc5 – MNF+ALS derivatives, sc6 – MNF+ALS and full-waveform data, sc7 – MNF+topographic indices, sc8 – MNF+full-waveform data, sc9 – MNF+all products; Marcinkowska-Ochtyra *et al.,* 2018a).

The potential of bigger datasets is assessed by, for example, the use of variable importance, which allows the most important ones to be assessed throughout the process and the most relevant ones to

be selected for optimization. This can be presented by, for example, a mean decrease in accuracy calculated for multi-temporal data to which topographic indices were included in the classification of Natura 2000 habitats (Figure 5). For habitat 6210, which occurs on steep slopes with southern exposure and high insolation, the three variables at the top of the variable importance plot are related to the specific type of substrate (contrary to the classification of habitat 6510).

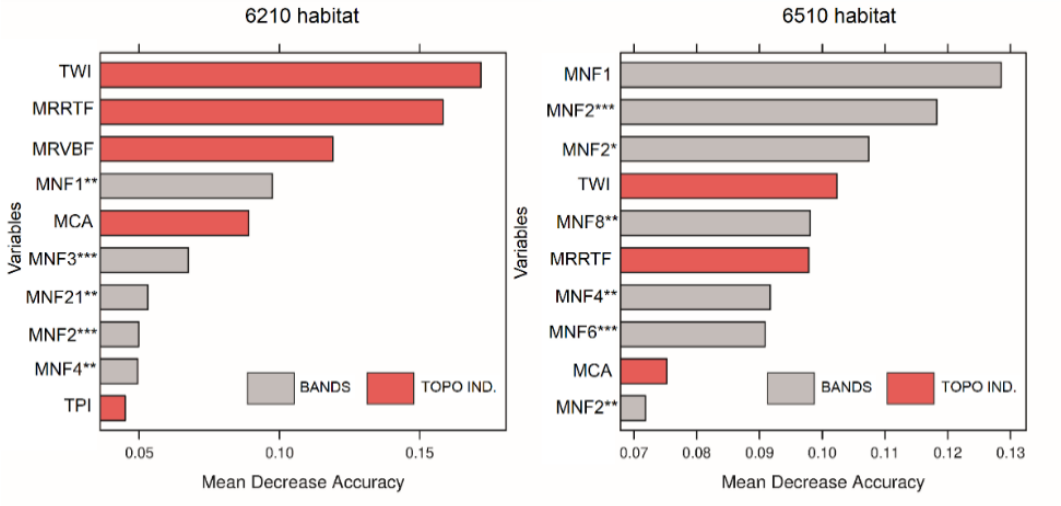


Figure 5. The ten most important variables in habitat mapping (*May, **July, ***September, MRVBF – Multiresolution Index of Valley Bottom Flatness, MRRTF – Multires. Ind. of Ridge Top Flatness, TPI – Topographic Position Ind., TWI – Topographic Wetness Ind., MCA – Modified Catchment Area; Marcinkowska-Ochtyra *et al.*, 2019).

### Algorithms

Currently, machine learning methods, e.g. Random Forest (RF) and Support Vector Machines (SVM) are popular in grasslands mapping. In general, SVM is used for large numbers of classes (about 20 [Marcinkowska-Ochtyra *et al.*, 2018b]), for several classes RF is more often used (e.g. Feilhauer *et al.*, 2014). When additional variables are included, it is also worth considering shortening the model training of the RF. In the case of grasslands, differences between object- (OBIA) and pixel-based approaches may also be of interest, as borders between communities and species are often vague. For example, on orthoimages and WorldView-2 data, Suchá *et al.* (2016) obtained better communities and species accuracy for OBIA with SVM (84%) than they did for pixel-based classifiers. For APEX and AISA Dual data, pixel-based SVM provided better accuracy (83%) than did OBIA (71–81%), while for Sentinel-2 the best was Maximum Likelihood (78% [Kupková *et al.*, 2017]). As can be seen, many factors as resolution, area, sample size and classes influence algorithm performance.

## Conclusions

Based on own experience and other work, we draw the following conclusions:

- **Platform** of data acquisition is essential for spatial resolution of images; even today's advanced satellite technologies cannot provide pixels of tens of cm.
- Each platform, or type of remote-sensing data, has its own advantages and drawbacks; these must therefore be taken into account when planning a grasslands mapping project (we should consider vegetation unit, detail of mapping, required accuracy, etc.).
- To achieve the best accuracy on the **species level** it is essential to combine data with very high spatial (cm) and spectral **resolution** (HS); increased temporal resolution can improve classification accuracy – it is recommended to combine data from the main months of the vegetation season (June, July, August and September). A similar relationship is evident in the classification of **habitats/communities** and **types of ecosystem**, but a whole set is not always

needed – it is important to choose the best terms. As the unit increases, high spatial resolution is no longer as important as high spectral resolution.

- When data of resolution below 1 m are not available, the main grass species can still be classified with rather high **accuracy** from aerial or satellite data with metre resolution, and a classification legend on the level of individual species can be used; however, species with low abundance will be classified with rather low accuracy (less than 60%).
- Testing of different **legends** (with different number of categories and different levels of generalization) is recommended to reach the best accuracy for different types of data and individual vegetation categories (with regards to the spatial resolution of the data).
- Collaboration between remote-sensing specialists and botanists is highly recommended for training and validation of data collection and legends elaboration.
- **Additional variables** can increase the accuracy of results, but it is important to optimize the classification process and decide which variables will be particularly important for the grassland considered, depending on their physiognomy and their preferred conditions.
- As for the different **classification methods**, OBIA seems to provide better results for extremely high spatial resolution data. Different pixel-based classifiers could work with different levels of reliability for different data and different grasslands categories.
- When planning a grasslands mapping project all mentioned **scales** should be considered and the most suitable data and methods should be selected for the study goal.

Finally, we conclude that remote sensing brings special features to grasslands monitoring and is a powerful tool in monitoring practice and nature preservation. However, remote-sensing specialists, organizations and companies, together with practitioners, will have to undertake further research to maximize the reliability of obtained products.

## Acknowledgements

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# Detection of mowing events from combined Sentinel-1, Sentinel-2, and Landsat 8 time series with machine learning

Lobert F.[1,2], Holtgrave A.-K.[3], Schwieder M.[1], Pause M.[2], Gocht A.[1], Vogt J.[4] and Erasmi S.[1]

*[1]Institute of Farm Economics, Thünen Institute, Bundesallee 63, DE-38116 Braunschweig; [2]Faculty of Environmental Sciences, Technische Universität Dresden, Helmholtzstr. 10, DE-01062 Dresden, Germany; [3]Institute of Rural Studies, Thünen Institute, Bundesallee 64, DE-38116 Braunschweig; [4]Department of Ecology and Ecosystem Management, Technische Universität München, Hans-Carl-von-Carlowitz-Platz 2, DE-85354 Freising, Germany*

## Abstract

The intensity of land use in permanent grasslands affects both biodiversity and important ecosystem services. Optical satellite systems have already proven to be suitable for area-wide detection of proxies of grassland management intensity, namely mowing events. However, clouds lead to considerable gaps in time series, resulting in an underestimation of the total number of events. SAR systems like Sentinel-1 (S1) can overcome this limitation, yet the information obtained is more complex to interpret. To test the synergy and complementarity of both sensor types for mowing detection, we computed high-density SAR and optical time series over three test sites in Germany covering detailed reference data on grassland management. For the growing periods in 2018 and 2019, we tested two binary, supervised machine learning algorithms, a convolutional neural network (CNN) and support vector machines (SVM), classifying sliding windows into *mown* and *not mown*. S1 VH/VV backscatter ratio, as well as Sentinel-2 (S2) and Landsat 8 (L8) normalized difference vegetation index (NDVI), were used as input features. Both models show promising results in detecting mowing events, where SVM performed slightly better. Overall, the approach shows a high potential for routinely mapping grassland management intensity over large areas in heterogeneous environments.

**Keywords:** mowing event detection, support vector machines, convolutional neural network, sensor fusion

## Introduction

Increasing management intensity of agricultural areas is an important driver for biodiversity loss. Comprehensive knowledge on these management intensities is a crucial factor for sustainable decision-making in landscape policy and planning (Foley *et al.*, 2005). The management intensity of grassland can be described by the mowing frequency on meadows (Weiner *et al*., 2011). However, it is unfeasible to obtain area-wide information on mowing frequencies, e.g. by interviewing farmers or by the on-site collection of data. Several studies have proved remotely sensed optical and radar imagery data to be a valuable data basis for this task. There is, as yet, no best practice, and suitable reference data are an important prerequisite for validation and optimization (Reinermann *et al*., 2020). This study aimed to test two machine learning algorithms for the detection of mowing events in combined time series of Sentinel-1 (S1), Sentinel-2 (S2), and Landsat 8 (L8) for test sites in three regions within Germany (central, North-East, South-West).

## Materials and methods

Comprehensive information on all management activities for a total of 56 meadows was provided for the test sites (Vogt *et al.*, 2019). Dense time series of satellite data were derived for the entire growing season in 2018 and 2019. For S1, one orbit was chosen per test site and the $\sigma^0$ VH/VV backscatter cross-ratio (CR) was processed. For S2 and L8, NDVI was calculated for all observations covering the test sites. Gaps induced by clouds and shadows were interpolated with a radial basis convolution filter using *FORCE* (Frantz, 2019). For all meadows, the median for the processed satellite data was derived using parcel boundaries. The time series were linearly interpolated to a 1-day interval and smoothed with a Savitzky-Golay filter. To translate the task into a supervised classification problem, shorter sequences were generated from the time series using a sliding window approach (Figure 1). If a mowing event happened on the middle day of a sequence, it was labeled as *mown*, otherwise as *not mown*. A length of 29 days was chosen to supply the classifier with information for 14 days before and after a

potential event and capture temporal trends. With a stride of one day, it was ensured that each day is the middle step of a sequence once. The class-imbalance was handled by random oversampling of the sequences which were labeled as *mown*.

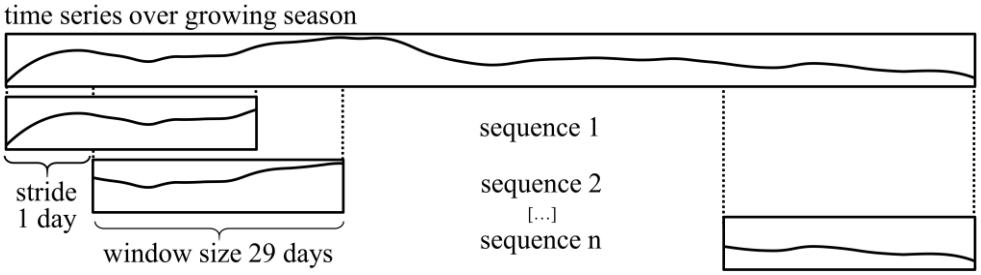


Figure 1. Schema of the sliding window approach.

Two machine learning algorithms were trained on the created dataset, classifying the sequences into *mown* and *not mown*: a SVM classifier and a 1-D CNN with three convolutional layers adapted from Wang *et al.* (2017). The models were implemented with *caret* and *Keras* with *TensorFlow* as backend. To estimate the models' ability to generalize the problem, a 10-fold cross-validation was conducted. Since the algorithms tend to classify consecutive time steps as events, these predictions were clustered and combined as a post-processing step. A temporal tolerance of 7 days was chosen for a prediction to be counted as true for the evaluation. All processing steps were carried out using R (R Core Team, 2020).

## Results and discussion

Table 1 shows a considerably higher recall for SVM than for CNN. The SVM model correctly detected 71.9% of the events whereas the CNN model only detected 57.8%. However, the CNN's predictions were more precise. For CNN, 59.8% of the predictions were true whereas only 54.3% for SVM. Summarizing recall and precision in the F1-score, the SVM outperformed the CNN with 0.615 compared to 0.579.

Table 1. Averaged results of the 10-fold cross-validation for both models.

| Model | Recall | Precision | F1-Score |
|---|---|---|---|
| SVM | **0.719** | 0.543 | **0.615** |
| CNN | 0.578 | **0.598** | 0.579 |

The confusion matrices reveal that SVM tends to overestimate the number of mowing events (Table 2). The CNN, in contrast, predicted fewer mowing events than present in the reference data. Compared to the high number of sequences that were *not mown*, the number of false positives is exceptionally low for both models.

Table 2. Confusion matrices for the 10-fold cross-validation for SVM (a) and CNN (b)

a)

| Prediction | Reference | | Total |
|---|---|---|---|
| | Not mown | Mown | |
| Not mown | 22567 | 48 | 22615 |
| Mown | 104 | 120 | 224 |
| Total | 22671 | 168 | 22839 |

b)

| Prediction | Reference | | Total |
|---|---|---|---|
| | Not mown | Mown | |
| Not mown | 22609 | 71 | 22680 |
| Mown | 62 | 97 | 159 |
| Total | 22671 | 168 | 22839 |

One explanation for the overestimation of SVM is the learning of a signal that often occurs during mowing events and seems to be necessary for an event to a certain point; e.g., this could be a drop in both NDVI and CR with a certain offset. However, the learned signal is not sufficient to classify an event unambiguously and occurs at other points in time. The moderate recall and precision for the CNN suggest a low degree of generalization. The learned signal appears along fewer mowing events, leading to a high number of omissions. Yet there are fewer occurrences of the learned signal unrelated to mowing events, resulting in fewer false detections compared to SVM. The recall value of the SVM

classifier is in the same order of magnitude as the results reported by Kolecka *et al.* (2018), who only used S2 imagery. This contradicts the assumption that the inclusion of S1 can significantly improve the mowing detection. Yet, a different method was used and only CR was tested as an S1-based feature.

## Conclusions

The input features from S1, S2, and L8 in combination with the tested algorithms are suitable for the detection of mowing events. The tested models performed differently. SVM detected more mowing events than CNN. However, the CNN's predictions were more precise and contained fewer false positives. Nevertheless, the accuracies show that the proposed method is not yet ready for operational use. Further research will tackle optimization tasks for both parameter selection and window sizes for the generated sequences. Other S1-based parameters like texture metrics and interferometric coherence could enhance the detection accuracy, just as adaptions of the CNN architecture to better fit the given problem.

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# Using yellowness in drone-based RGB images to map buttercup cover in an upland pasture

Schneider M. K.[1] and Willems H.[2]

*[1]Forage Production & Grassland Systems, Agroscope, Reckenholzstrasse 191, CH-8046 Zürich, Switzerland; [2]Büro Alpe GmbH, Eichholzweg 11, CH-3053 Lätti, Switzerland*

## Abstract

The reduction of unwanted plant species in pastures is a persistent objective of grassland management. Evaluating different management options requires the assessment of the spatial coverage of the unwanted species. Here, we evaluate the use of drone-based images to quantify the cover of buttercup (*Ranunculus acris*) in an upland pasture (1654 m asl.) in the Central Swiss Alps. Buttercup is of primary concern because it is moderately toxic and avoided by grazers. Between 2016 and 2020, we conducted a randomized complete block trial with ten different treatments (combinations of grazing, mowing, liming, herbicide and overseeding) in four repetitions. Aerial images were taken annually at the peak of buttercup flowering, with a fixed-wing autonomous drone (senseFly eBee) carrying an RGB camera (Canon S110 and from 2019, senseFly S.O.D.A.) and post-processed using Pix4Dmapper. Yellowness was calculated as the percentage of yellow pixels using optimized thresholds on the RGB channels. The correlation coefficient between the yellowness of the images and the share of buttercup estimated by an independent observer was above 0.85 for the last two years. The newer S.O.D.A. camera outperformed the S110 due to its higher resolution, which was shown to be crucial for this kind of assessments.

**Keywords:** subalpine pasture, weed cover, drone, RGB images

## Introduction

Around one third of the agricultural land in Switzerland is located near or above the alpine treeline and only used during summer (Lüscher *et al.*, 2019). It is grazed by ruminant livestock and characterised by shallow soils and undulating topography. Since there are fewer management options available in a pure grazing system than in mixed mowing-with-grazing, and since the harsh climate limits the growth of productive grasses, sward composition is often of primary concern. Buttercup (*Ranunculus acris*) is a common forb in many pastures that are fertilized with livestock manure. It produces the glycoside ranunculin which causes mouth blistering, intestinal disorder and potentially respiratory failure (Lamoureaux and Bourdôt, 2007). It is therefore avoided by grazing livestock and has a competitive advantage over more palatable species. Hence, buttercup can reach substantial cover in grazed pastures, thereby decreasing forage quality and usage. However, adequate regulation strategies to reduce its abundance are lacking. Since the assessment of species cover over large areas is labour-consuming, we tested whether remote sensing can help to monitor the effects of regulation strategies already developed for invasive grasses and large-leaved forbs in grassland (see for example Malmstrom *et al.*, 2017 and Lam *et al.*, 2020).

## Materials and methods

From 2016 to 2020, a field experiment was conducted on a summer pasture in the Meien valley in the Central Swiss Alps (46°44′30.1″ N, 8°29′14.8″ E) at 1654 m asl. The site is a slightly undulating valley bottom formed by the sedimented gravel of the river Meienreuss and covered by only 5-10 cm of organic topsoil. The pasture is grazed by dairy cows twice during summer in a rotational grazing systems. The sward is dominated by grasses (50-70% cover, mainly *Agrostis capillaris*, *Festuca rubra* and *Phleum rhaeticum*), buttercup (10-45%), and other forbs (10-25%, mainly *Alchemilla vulgaris*). Ten treatments were applied on subplots of 40 $m^2$ in a randomized block design with four repetitions. Aerial images were taken annually at the peak of buttercup flowering, using a fixed-wing autonomous drone (eBee, senseFly, Cheseaux-sur-Lausanne, Switzerland) flying around 50 m above ground and carrying an RGB camera. Initially, a Canon S110 with 12.1 MPixels was used, which had to be replaced by a newer senseFly S.O.D.A. with 20 MPixels in 2019. The images were merged using Pix4Dmapper (Pix4D SA, Prilly, Switzerland) to a resolution of 2 cm and geolocated using ground control points. The yellowness

in all images was derived using threshold values of >167.9 for red, >170.7 for green and <86.4 for blue. These values were obtained by optimizing the average correlation coefficient over all five years. The obtained values were compared to estimates of buttercup cover on the ground made by a single observer every year.

## Results and discussion

Image quality differed between years with lowest quality in 2017 and 2018 and the best in 2019 and 2020. As examples, the data of 2018 and 2020 are shown in Figure 1. In 2018 the timing of the capture was not optimal right after the mowing. In addition, the Canon camera used in that year produced relatively blurred images. In 2020, the area was captured in full bloom and with the newer S.O.D.A. camera. This resulted in much more detectable yellowness in 2020 than in 2018.

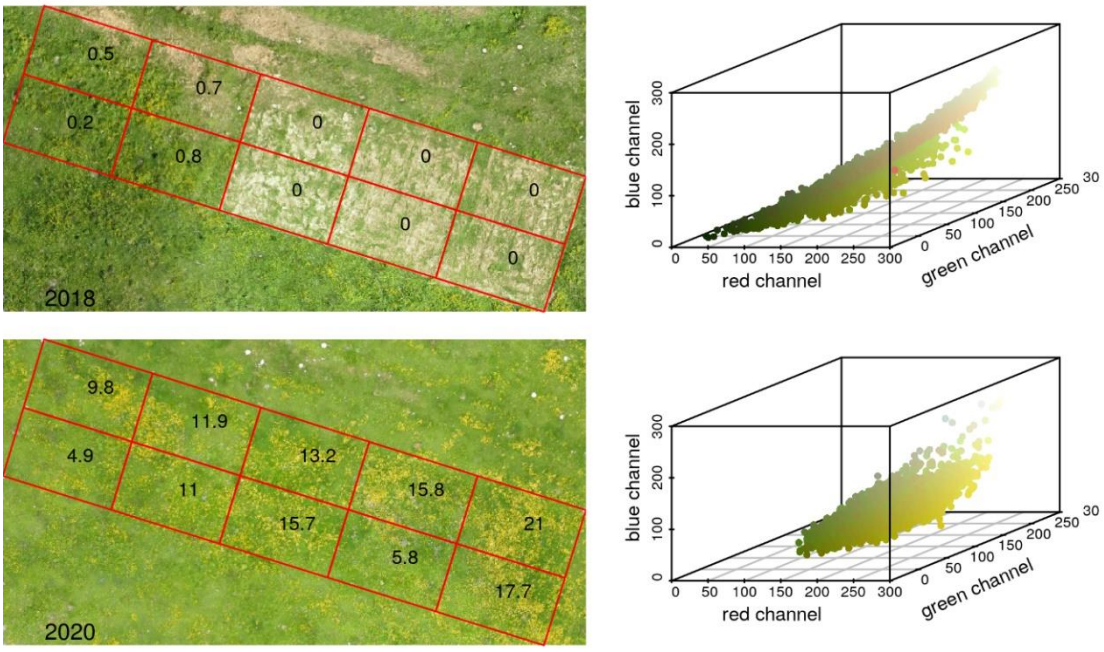


Figure 1. Aerial image of one block composed of ten subplots (left) and scatterplot of the colour values (right) in 2018 and 2020. Numbers in the left panel show yellowness.

The yellowness of the images generally showed good agreement with the share of buttercup as estimated by an independent observer (Figure 2). Correlation coefficients ranged from 0.25 to 0.93. The low correlations in 2017 and 2018 were mainly due to many zero values due to inappropriate timing of the image capture. In 2019 and 2020, when the S.O.D.A. camera was used and the timing was optimal, the correlation coefficients were above 0.85.

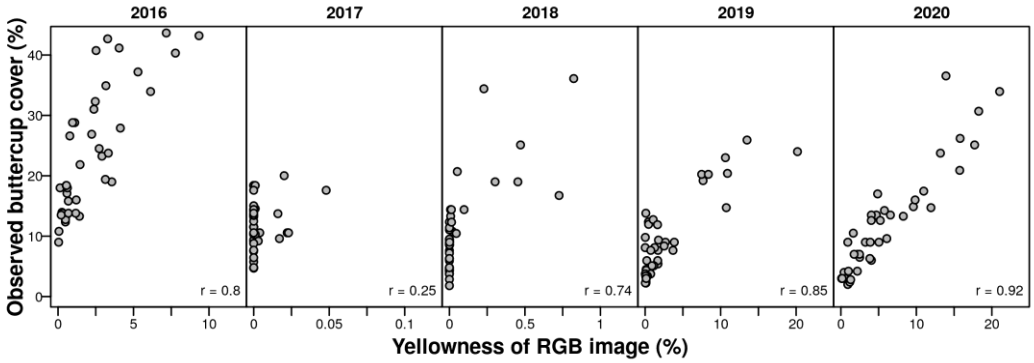


Figure 2. Correlation between the percentage yellowness in RGB images and the observed percentage cover of buttercup on the ground for the years 2016 to 2020. For each year, the coefficient of the correlation is given.

While the correlation between yellowness and observed buttercup cover was high, the absolute relationship varied between years. This can be seen in the different ranges of the x-axis in Figure 2. For example, an observed cover of 40% in 2016 corresponded to a yellowness of the image of 10%. In 2020, an observed cover of 35% corresponded to a yellowness of 20%. Although buttercup cover was observed by the same person every year, some fluctuation cannot be ruled out. The data of 2019 and 2020, nevertheless, suggest that yellowness can be used as an indicator of buttercup cover across years, if the camera and flight setup remain stable. The fact that none of the relationships followed the 1:1 curve demonstrates the importance of quantitative ground measurements.

## Conclusions

Yellowness in RGB images is a valid indicator for yellow plant species such as buttercup. If a single species should be detected, it is important that it is the dominant flowering species. The accuracy of the indicator depends, importantly, on the quality of the images, namely the resolution, contrast and blurring. The data show that a unique relationship between yellowness of the image and observed buttercup cover can only be established across multiple years if a similar flight setup has been used. Nevertheless, the study demonstrates the potential of drone-based images in assessing the cover of dominant weed species.

## Acknowledgements

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# Mapping invasive *Lupinus polyphyllus* Lindl. in grasslands from UAV-borne remote sensing images

Wijesingha J., Astor T., Schulze-Brüninghoff D. and Wachendorf M.

*Grassland Science and Renewable Plant Resources, Universität Kassel, Steinstraße 19, D-37213, Witzenhausen, Germany*

## Abstract

*Lupinus polyphyllus* Lindl. (lupine) is one of the most invasive plants in European grasslands. Information about up-to-date coverage of invasive lupine is essential for effective planning of control activities and evaluating biodiversity states of the grasslands. Thus, this study focused on developing a workflow to map lupine spatial coverage using the unmanned aerial vehicle (UAV)-borne remote sensing (RS) images instead of manual digitising of aerial images. The study was conducted at an experimental grassland setup in the UNESCO biosphere reserve Rhön in Germany. UAV-borne RGB, thermal images and their derivatives (e.g., canopy height model, texture, vegetation indices, etc.) were utilized. RS images were segmented to obtain image objects, and attributes for each image object were computed. Then image objects were classified using a random forest classification model based on objects' attributes. The mean prediction accuracy of the classification models was 89%. The classification-based lupine coverage maps showed a ±5 % disagreement in the lupine area compared to the image digitising method. Overall, the developed workflow with UAV-borne RS images demonstrated that it could be adopted for accurate mapping of lupine in grasslands in an efficient way.

**Keywords:** invasive plant species, unmanned aerial vehicles, object-based image analysis, spatial coverage mapping, grassland

## Introduction

Biodiversity in many ecosystems in the world is threatened due to biological invasion by alien plant and animal species. In Europe, 3749 alien plants are currently naturalized in different ecosystems, and 37.4 % of them occur in grassland habitats (Lambdon *et al*., 2008). *Lupinus polyphyllus* Lindl. (hereafter referred to as lupine) native to the western North America, is a widespread invasive species in European grasslands (Fremstad, 2010). In the last few decades, the UNESCO biosphere reserve Rhön in Germany was invaded by lupine. This has changed species-rich grasslands into species-poor dominance (Otte and Maul, 2005). Thus, knowledge of the spatial distribution of lupine in the grasslands is crucial for handling invasive lupine control activities and examining their efficacy. Manual digitalisation of aerial images is the current method employed to obtain spatial coverage of the lupine distribution in grasslands (Klinger *et al*., 2019), but its time and labour demands mean this practice is not adequate to provide up-to-date lupine coverage. Thus, this study proposed an approach to map spatio-temporal coverage of lupine in the grasslands using very high-resolution images acquired using an unmanned aerial vehicle (UAV) as an effective alternative.

## Materials and methods

The study was carried out in the two lupine invaded grassland fields in Germany's Rhön biosphere reserve. In both fields, rectangular plots of 1500 m² were chosen as study areas, and 15 small plots of 64 m² were established within a 5 x 3 grid pattern. Three cutting dates in summer 2019 (12 and 26 June and 9 July) were randomly assigned to 5 replicated plots. At each cutting date in each grassland field, the UAV-borne images were acquired using a DJI-Phantom IV quadcopter (DJI, China). The UAV was equipped with a commercial-grade RGB camera and a thermal camera (FLIR Vue Pro R). The UAV was flown at 20 m altitude, which yielded 1 cm and 2 cm ground sampling distances from RGB and thermal cameras. All the UAV-borne images were processed to obtain a canopy height model (CHM) raster, a point density (PD) raster, an RGB ortho-mosaic, and a thermal ortho-mosaic using Agisoft PhotoScan software (Agisoft LLC, Russia). RGB mosaic image was then converted to hue, intensity, and saturation mosaic (HIS mosaic).

Object-based image analysis technique was utilized in this study. The CHM raster, PD raster and hue image from HIS ortho-mosaic were used to obtain image objects using GRASS GIS software. In total,

32 attributes (4 geometric and 28 image-based) were generated for each image object based on the derived raster's mean and standard deviation values. 10% of the total image objects were manually labelled as lupine and non-lupine, and those labelled objects were employed to build supervised classification models using a random forest algorithm. Six classification models were trained and tested by holding out a dataset from each date and site combination. Later, all labelled data were employed to train a final model for predicting label for the remaining 90% of the objects' labels. Based on predicted labelled objects, the lupine coverage map for each site and each date were generated. Area-wise and pixel-wise comparison of classification based lupine map and the manually digitized lupine map were conducted.

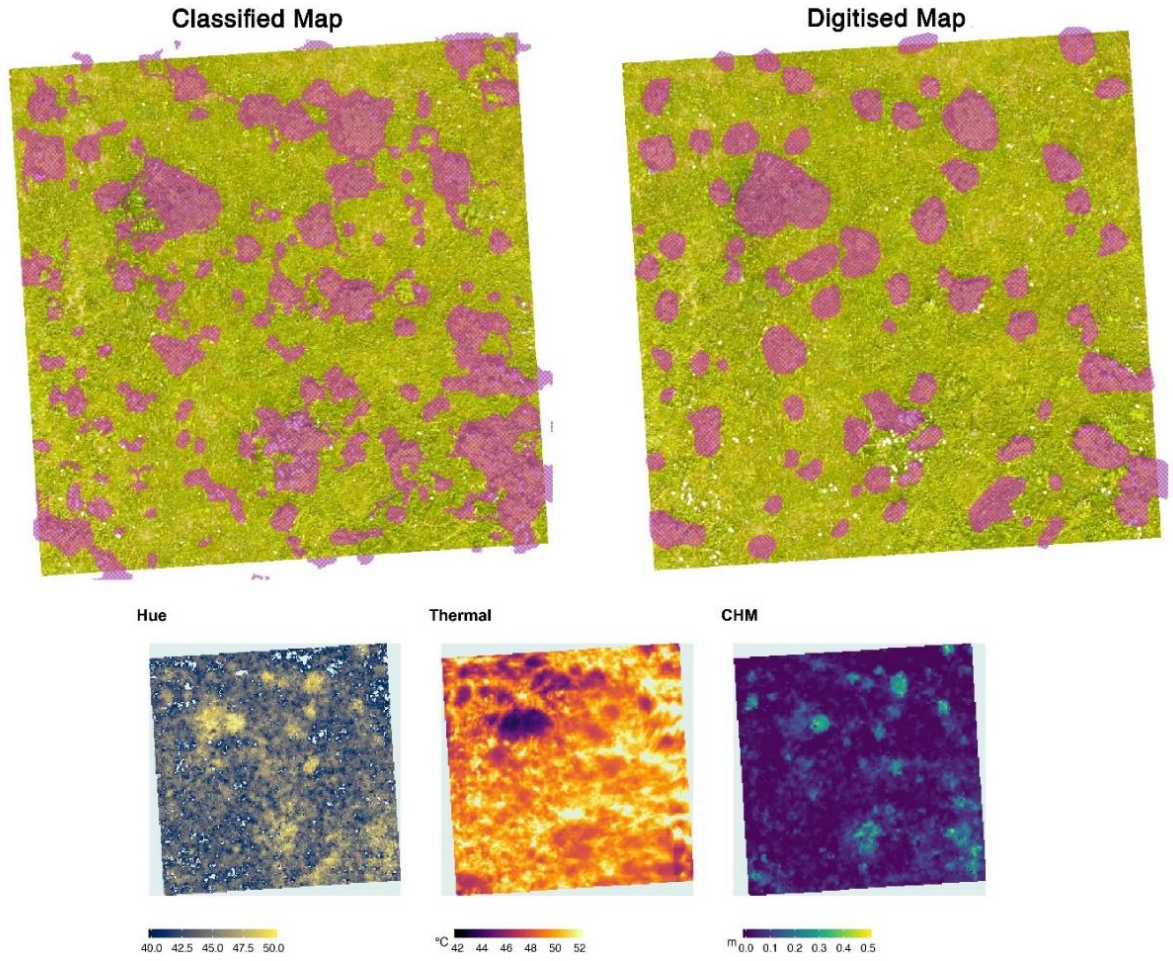


Figure 1. Lupine coverage map (pink patches) overlaid on the RGB image from the proposed classification method (top left) and manual digitising (top right). The hue image (left), thermal image (middle), and canopy height model (right) for the same area are shown at the bottom.

## Results and discussion

According to the six classification model results, the models' overall accuracy varied between 78% and 97%. Except for one model, all other five models resulted in less than 9% false-positive-rate. In each instance, the trained model was tested using a dataset from a different location and specific date (sward maturity). Hence, overall performances of the six models revealed high model stability and robustness across time and space. This indicates that developed models could be easily transferred to other grassland sites of varying maturity.

The final model with all data showed 94.2% training accuracy, and canopy height (CHM) was the most vital attribute to distinguish lupine and non-lupine objects. This indicated the one advantage of UAV-borne images: they allow deriving of height information that can be helpful to separate two plants based on height differences. However, the attributes based on thermal images did not provide a significant impact on the classification model. The area-based comparison between the lupine coverage map from

the proposed methodology and the manual digitizing method revealed a maximum of 5% of the total lupine coverage. A relative number of no-difference pixels from two lupine maps always showed more than 80% of pixels from both maps matched their labels.

## Conclusions

The proposed approach demonstrated that spatio-temporal coverage of lupine in grasslands could be mapped efficiently using high-resolution images acquired from UAV. Moreover, the classification model can be transferred to other regions, thereby overcoming the limitations of the standard way of lupine mapping. Finally, the developed procedure can be adopted to map other invasive species in grasslands and other ecosystems.

## Acknowledgements

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# Using image analysis and machine learning to estimate sward clover content

Hennessy D.[1,2], Saad M.[2,3], Mac Namee B.[2,3], O'Connor N.E.[2,4], McGuinness K.[2,4], Albert P.[2,4], Narayanan B.[2,3], Fitzpatrick E.[1] and O'Connor A.H.[1,2]

*[1]Teagasc, Animal and Grassland Research and Innovation Centre, Moorepark, Fermoy, Co. Cork, Ireland; [2]VistaMilk Research Centre, Animal and Grassland Research and Innovation Centre, Moorepark, Fermoy, Co. Cork, Ireland; [3]Insight Centre for Data Analytics, UCD School of Computer Science, University College Dublin, Belfield, Dublin 4, Ireland; [4]Insight Centre for Data Analytics, School of Electronic Engineering, Dublin City University, Ireland*

## Abstract

Incorporating white clover (*Trifolium repens* L.) into grass swards can reduce the requirement for nitrogen (N) fertilizer due to its ability to fix atmospheric N and can also result in increased dairy cow milk production through increased herbage quality. Quantifying sward white clover content is laborious and time consuming. The objective of this study was to capture images and data to train a machine learning model to estimate sward white clover content. A dataset containing 515 images of grass and grass-white clover swards and associated ground-truth data was developed. A deep learning model was trained to estimate the content and percentages of grass, white clover and weed components with good accuracy directly from Irish sward images.

**Keywords:** biomass prediction, machine learning, deep learning, grass, white clover

## Introduction

Incorporating white clover into grass swards can reduce the requirement for nitrogen (N) fertilizer due to its ability to fix atmospheric N and can result in increased dairy cow milk production through increased herbage quality (Egan *et al*., 2018). Quantifying sward white clover content is laborious and time consuming, however. Recently there have been successful efforts to use machine learning to predict the dry matter (DM) yield of clover and grass directly from ground-level images. These efforts aim to provide a fast and non-destructive approach to biomass yield prediction that will help farmers to optimize management decisions including fertilizer usage, seeding density, and crop rotation. Mortensen *et al*. (2017) detail their approach to segment 28 hand-annotated images to classify grass and clover individually from soil, followed by step-wise linear regression to estimate dry biomass from the segmentation. Søren Skovsen *et al*. (2017) and (2018) used fully convolutional networks (FCNs) to semantically segment synthetically simulated grass-clover images. They then performed segmentation on real images and used the resulting pixel-wise percentages to estimate the biomass composition. Previously, Narayanan *et al*. (2020) presented results from a more direct pixel-to-biomass estimation approach using a publicly available grass-clover image dataset collected from farms in Denmark (Soren Skovsen *et al*., 2019). The objective of this study was to capture an image dataset in Ireland to train a machine learning model to estimate sward white clover content.

## Materials and methods

A total of 515 images with ground truth were captured from grass-only and grass-white clover plots (9 m ×1.5 m) at Teagasc, AGRIC, Moorepark, Fermoy, Co. Cork, Ireland. Each image corresponded to a 0.5×0.5 m quadrat with 5-6 images taken from each plot. Images were captured between 21st and 23rd July 2020. There were 13 grass-only plots and 13 grass-white clover plots in each of 4 replicates. Herbage within each quadrat was harvested at 2-4 cm above ground level using a Gardena hand shears (Accu 60, Gardena International GmbH, Ulm, Germany) immediately after image capture. Fresh weight was recorded and harvested herbage was separated, dried and weighed to give DM yield plus percentage composition of grass, clover and weeds as ground truth. Figure 1 shows sample images from this dataset.



Figure 1. Sample of collected images in the Irish dataset.

*Data pre-processing*: Working with convolutional neural networks requires a standard input image size and shape across images. Accordingly, all the images in the dataset were cropped to the quadrat boundaries, resized to a fixed size by padding them, and standardized into square shapes. Thus, we were able to retain the aspect ratio of the images when dynamically resizing them during training. We used all 515 images after pre-processing for this preliminary analysis, dividing them into a training set (412 images) and a validation set (103 images).

*Experiments*: Two experiments were performed to establish the suitability of using these images for future experiments in biomass estimation and other phenotype analyses. The first experiment used the model from Narayanan *et al*. (2020), trained on the images from Danish farms using ground-truth data imputed with the mean imputation method (which resulted in the best performance described in that paper), to make predictions for the 515 squared images. The ground-truth values for grass-clover and weeds are expressed in percentages, and take a value in the range [0, 100]. In the second experiment the model was re-trained on the Irish dataset. Briefly, all of the convolutional layers of the VGG-16 architecture with pretrained weights from Imagenet were used for transfer of feature representations, and the weights were frozen. The fully connected layers and the output layer for classification in VGG-16 were replaced with two fully connected layers (reLu activations on 4096 and 256 neurons respectively), each followed by a batch normalization, and a final softmax output layer with three neurons for three targets, i.e. grass, clover and weed percentages. The model was trained without any data augmentation or dataset expansion.

The performance was measured using root mean square error (RMSE) and mean absolute error (MAE) of the estimated percentages of sward biomass content compared to ground truth. All experiments were performed in the Python programming language using the scikit-learn (www.scikit-learn.org) and tensorflow.keras (www.keras.io) packages.

## Results and discussion

Table 1 summarizes the performance of the Narayanan *et al*. (2020) model in predicting the sward content of the Irish dataset when firstly pre-trained on the Danish dataset and secondly re-trained on the Irish dataset. The performance of the model pre-trained on the Danish dataset had an overall MAE of 15.19% and a RMSE of 21.26%. This is primarily because the data distribution for the components in the Irish dataset was different to that of the Danish dataset which had a greater number of components. When the model was re-trained on the Irish dataset, the performance was improved and had an overall MAE of 4.74% and a RMSE of 7.57%.

Table 2. Performance of the model from (Narayanan *et al*., 2020) on the Irish dataset.

| Training approach | Performance Measure | Grass | Clover | Weeds | Overall |
|---|---|---|---|---|---|
| (1) Pre-trained on the Danish dataset | MAE (%)* | 20.15 | 22.29 | 3.13 | 15.19 |
| | RMSE (%) | 24.87 | 26.68 | 5.06 | 21.26 |
| (2) Re-trained on the Irish dataset | MAE (%) | 6.34 | 5.09 | 2.79 | 4.74 |
| | RMSE (%) | 9.71 | 8.69 | 4.32 | 7.57 |

*MAE = mean absolute error; RMSE = root mean square error

## Conclusions

While there is room to improve these results, they support the hypothesis that machine learning methods can be used to predict sward composition and other phenotypes from images, offering an alternative to the current time-consuming, expensive, destructive approaches.

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# First results of applying UAV laser scanning to a cattle grazing experiment

Hütt C.[1], Bolten A.[1], Hohlmann B.[2], Komainda M.[2], Lussem U.[1], Isselstein J.[2] and Bareth G.[1]

*[1]GIS & Remote Sensing Group, Institute of Geography, University of Cologne, Germany; [2]Grassland Science, Department of Crop Sciences, Georg-August-University Göttingen, Germany*

## Abstract

Remote sensing, especially from unmanned aerial vehicles (UAVs), has gained popularity for monitoring grassland growth dynamics over space and time, enabling location-specific management optimization. A new generation of LiDAR sensors mounted on UAVs could potentially overcome the drawbacks of using optical imaging as the information basis. For this study, a Riegl miniVUX-1 UAV installed on a DJI Matrice 600 pro was flown over a cattle grazing experiment. Promising initial results show a moderate correlation to rising plate meter measurements.

**Keywords:** LiDAR, grassland monitoring, grazing, UAV, laser scanning, grassland

## Introduction

Determining grassland biomass over leniently stocked, and therefore very heterogeneous pastures (Schellberg *et al.*, 2008) is a demanding task (Safari *et al.*, 2016). The precise knowledge of grass biomass and its variability within grazing plots is crucial to meet the grazers' feed requirements and assess other ecosystem services demanded by the consumer, such as biodiversity and animal welfare (Stampa *et al*., 2020).

In particular, structure from motion (SfM) analysis of images acquired by unmanned aerial vehicles (UAVs) has gained considerable attention as a tool to generate the required geoinformation (e.g., Grüner *et al*., 2019). However, the approach has the disadvantages of being computationally intensive, having limited coverage, and multi-temporal acquisitions or a model of the ground are needed.

A promising alternative could be light detection and ranging (LiDAR) (Jin *et al.*, 2021), which is known to be sensitive to the biomass of crops (Ehlert *et al.*, 2008) and grassland biomass (Schulze-Brüninghoff *et al.*, 2020). Recent advancements in sensor development allow installing LiDAR scanners on UAVs. Such systems could overcome the disadvantages named above and determine the grassland growth spatially explicit (Wang *et al.*, 2017).

The present study demonstrates the feasibility of acquiring a LiDAR point cloud using a UAV-mounted LiDAR over the cattle grazing experiment 'Forbioben' in Relliehausen, Germany.

## Materials and methods

The study site is the experimental long-term cattle grazing experiment 'Forbioben' of the University of Göttingen, situated in Relliehausen, Germany (N 51° 46' 56, E 9° 42' 14). It comprises paddocks managed in a put and take system according to three stocking rates, each replicated thrice in a randomized block design and a paddock size of 1 ha each. The stocking rates vary from moderate, lenient, and very lenient based on regular sward height measurements.

This study's sensor system is a Riegl miniVUX-1 UAV Laser Scanner, with an Applanix-15 inertial measurement unit (IMU) integrated on a DJI Matrice 600 pro UAV. The flight campaign was planned using the drone mission planning software UgCS, which allowed complete flight automation. The LiDAR acquisition parameters are controlled via RiAquire, which is embedded in the LiDAR/IMU system. For postprocessing, GPS correction data was logged using the RTK GPS base station TOPCON GR-5 during the flight. The data was later combined in the POSPac UAV Software to estimate the UAV position and orientation with very high precision (~5 cm) throughout the flight. Based on the UAV trajectory's precise estimation, a first version of the LiDAR Point cloud can be generated. The UAV's position is then further refined using the LiDAR point cloud in RiPrecison software, which is integrated into Riegl's processing environment RiProcess. Characteristics of the flight and the resulting point cloud can be found in Table 1.

Table 1. Flight characteristics and point cloud statistics of the UAV LiDAR flight carried out over the Relliehausen test site.

| | |
|---|---|
| Date and start time of the flight | 30.6.2020, 11:32 am |
| Approx. flight time | 12 min. |
| Flight height: above ground / above mean sea level (min-max) | 40 m / 205-275 m |
| Flight Speed | 5 m/s – 18 km/h |
| Flight distance | 2.8 km |
| Covered area | 14 ha |
| Distance between scan lines | 80 m |
| Number of collected points | ~15 Million |
| Average point density over the test site | 84 Pts/m² |

Analysis of the point cloud consisted of classifying the ground points and then normalizing all points to height over the ground. Merging of the strips was applied after this step, minimizing the influence of potential suboptimal strip alignment to the height above ground value.

The ground measurements were performed using a rising plate meter (RPM) to determine the compressed sward height (CSH) as a productivity proxy. The CSH was determined on 90 geo-referenced positions distributed over the whole experiment. The measurements' exact location was determined with the same TOPCON GR-5 GPS as above, but in Base / Rover constellation, resulting in a cm accuracy and matching the point cloud's georeference.

## Results and discussion

The point cloud's mean height over the ground was calculated in a 1.25 m buffer around the 90 RPM measurements. The resulting scatter plot with this mean value and the CSH is shown in Figure 1. It was generally possible to relate the LiDAR mean height above ground to the RPM measurements with a moderate $R^2$ of 0.49. However, as shown in Figure 1, the mean LiDAR height above ground underestimates the CSH. The reason for that finding is most likely due to the limited capabilities of the LiDAR to penetrate entirely through the grass sward. As an active system, the LiDAR UAV is independent of sun-induced illumination, and therefore very flexible considering the acquisition environments (Ehlert *et al.*, 2008). Compared to the computational heavy SfM approach (Grüner *et al.,* 2019), the UAV LiDAR postprocessing computational needs are only a fraction, making it possible to have the resultant geoinformation right after the campaign.

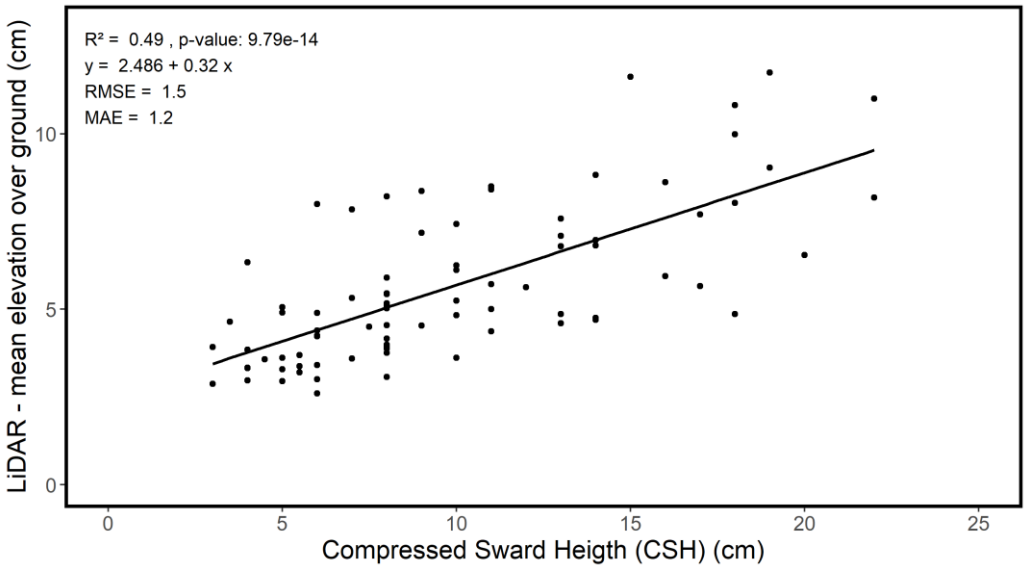


Figure 1. Scatter plot of the mean LiDAR height over ground (1.25 m buffer) with the compressed sward height, measured with a rising plate meter.

## Conclusions

The ability to predict CSH measurements from LiDAR would make it possible to estimate biomass and other important grassland properties from one flight and immediately after the flight. Therefore, the first investigation of UAV laser scanning shows a high potential to be a valuable grassland cattle management tool, but further experiments are needed to explore the capabilities of this approach in more detail.

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# Assessment of rangeland condition in a dryland system using UAV-based multispectral imagery

Amputu V.[1], Tielbörger K.[1] and Knox N.[2]

*[1]University of Tübingen, Auf der Morgenstelle 5, Tübingen, 72076, Germany; [2]Namibia University of Science and Technology, Storch Street 13, Windhoek, 9000, Namibia*

## Abstract

Dry savannahs are water-limited and under increasing anthropogenic pressure. Thus, considering climate change and the unprecedented pace and scale of rangeland deterioration, we need methods for assessing the status of such rangelands that are easy to apply, yield reliable and repeatable results, and can be applied over large spatial scales. Global and local scale monitoring of rangelands, through satellite data and labour-intensive field measurements respectively, are limited in accurately assessing the spatiotemporal heterogeneity of vegetation dynamics to provide crucial information that detects degradation in its early stages. Fortunately, newly emerging techniques such as unmanned aerial vehicles (UAVs), associated miniaturized sensors and improving digital photogrammetric software allow us to transcend these limitations, but they have not yet been extensively calibrated with rangeland functional attributes. In our study, we fill this gap by testing the relationship between UAV-acquired multispectral imagery and field data collected in discrete sample plots in a Namibian dryland savannah along a degradation gradient. The first results are based on a supervised classification performed on the ultra-high resolution multispectral imagery to distinguish between rangeland functional attributes, with a relatively good match to the field observations. Integrating UAV-based observations to improve rangeland monitoring could greatly assist in climate-adapted rangeland management.

**Keywords:** arid savannah, degradation gradient, drone, ground-truthing, narrow-band sensor, supervised classification

## Introduction

Land degradation in drylands remains one of the most serious environmental problems (Mansour *et al.,* 2012), especially because productivity is already constrained by limited moisture availability (Millennium Ecosystem Assessment, 2005; Middleton, 2018). Despite their low productivity, their structurally and functionally diverse ecosystems serve as habitats for wildlife, are suitable for livestock rearing, play a dominant role in carbon sequestration, and support over two billion people (Smith *et al*., 2019). Considering climate change and the unprecedented pace and scale of land degradation, it is crucial that methods assessing the status of such rangelands are easy to apply, yield reliable and repeatable results and can be applied over multiple spatial and temporal scales to detect degradation in its early stages. Extensive progress has been made over the last two decades to integrate multiscale information for ecologically relevant observations that accurately map and monitor indicators of vegetation condition to provide answers to ecological questions (Lawley *et al*., 2016; Karl *et al.*, 2017; Díaz-Delgado *et al*., 2019; Gillan *et al*., 2020). Unmanned aerial vehicles (UAVs), better known as drones, with associated sensors are receiving increasing attention from the ecological research community for monitoring vegetation and other ecosystem components (Assmann *et al*., 2019; Gillan *et al*., 2019). However, the relevant data processing and analysis methods are still largely ad-hoc, and their application still requires standardization and extensive calibration (Gallacher, 2019) if they are to be integrated for long-term monitoring. Our study evaluates the applicability of UAV-based multispectral imagery to assess rangeland status in a dry savannah along a degradation gradient in Namibia.

## Materials and methods

As a typical example of dryland systems, the research was conducted in Namibia, the driest country in sub-Saharan Africa to assess rangeland condition. A MicaSense Rededge MX sensor (www.micasense.com) mounted on a DJI Phantom 3 Advanced (www.dji.com) drone was used to acquire imagery along a 1500 m degradation gradient with increasing distance away from a water point. The multispectral sensor captures images at 5 spectral bands (Blue – 475@20nm, Green – 560@20nm, Red – 668@10nm, Red edge – 717@10nm and Near infrared – 840@40nm), with radiometric

calibration achieved through the use of a reflectance calibration panel and irradiance sensor (www.micasense.com). The imagery was acquired in January and March 2020 (early and mid-growing season respectively) using the Pix4DCapture (www.pix4d.com) flight planning application at 80 m above ground level, resulting in a 5.8 cm/ pixel resolution. This ultra-high spatial resolution imagery was processed in Pix4DMapper Pro (Pix4D, Switzerland, V3.3) to generate reflectance maps that were analysed in Environment for Visualizing Images (ENVI) software, for supervised classification of the imagery into three rangeland functional attributes (RFAs) (bare, non-woody plants, and woody plants). Field-based assessments using the adapted line-point intercept method (Herrick *et al*., 2017) to estimate the RFAs cover were done in 100 $m^2$ plots along the degradation gradient for ground-truthing.

## Results and discussion

The UAV estimated proportional cover of the three rangeland functional attributes match relatively well with the field-based observations, especially during the early growing season. As expected, plot 1 that is closest to the water point has higher proportion of bare ground cover, which declined with distance away as the season progressed. During the mid-growing season, the field estimates did not record bare ground for plot 5 and 9, largely because observations are bound to sampling points, a limitation that may mislead the management of rangelands. This underlines the need to calibrate and integrate the rapidly advancing UAV technology, which offers a complete overview of the area of interest with great flexibility and sufficient accuracy for rangeland monitoring (Laliberte *et al*., 2010) and addressing a wide variety of ecological phenomenon (Rango *et al*.,2009; Barnas *et al*., 2019).

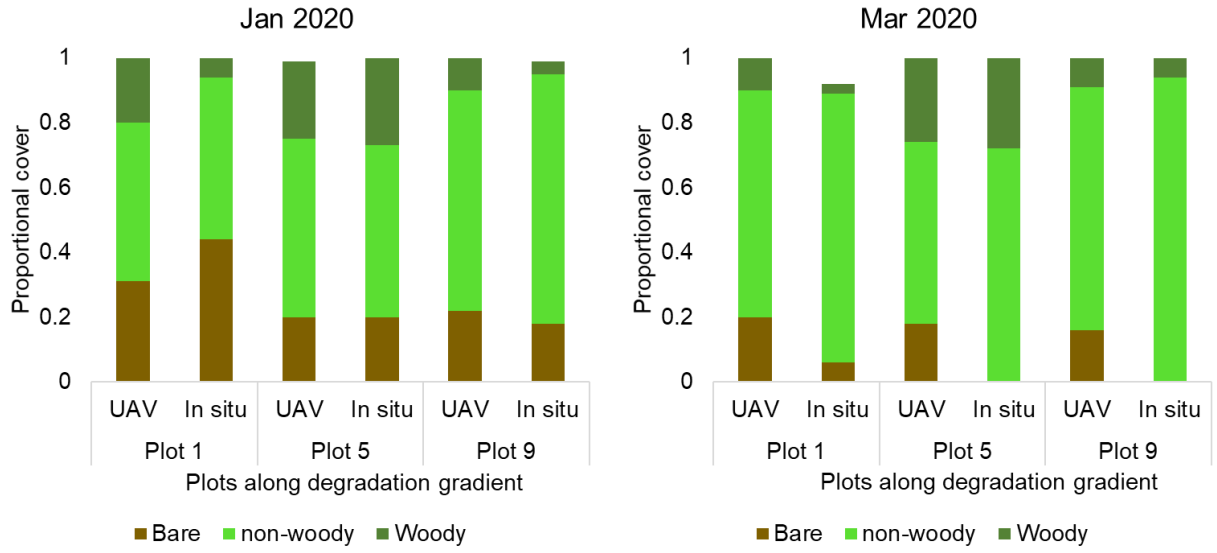


Figure 1. UAV and *in situ* estimated proportional cover of rangeland functional attributes (RFAs) for early and mid-growing season.

## Conclusions

Based on the preliminary results there seems to be a relatively good match between the field observations and the UAV estimated rangeland functional attributes, with the latter method being more comprehensive as it is not restricted to observation points. This promising technology offers unbiased, more accurate, and efficient means for monitoring the status of rangelands at multiple spatial and temporal scales.

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# Permanent grassland established on eroded soils: floristic composition of different sections of a hillside after 27 years of sward naturalization following sowing

Matyziute V. and Skuodiene R.

*Lithuanian Research Centre for Agriculture and Forestry, Vezaiciai Branch, Gargzdu str. 29, 96217, Klaipeda district, Lithuania*

## Abstract

The objective of this study was to estimate changes in phytocenoses' floristic composition in different parts of a hillslope following 27 years of naturalization after sowing. In 1993 a mixture of perennial species was sown on a south-facing slope, soil type Eutric Retisol (slightly eroded). Seed mixture was timothy (*Phleum pratense*) 20%, red fescue (*Festuca rubra*) 20%, meadow grass (*Poa pratensis*) 20%, white clover (*Trifolium repens*) 20%, and bird's-foot trefoil (*Lotus corniculatus*) 20%. In 2020 the floristic composition of the resulting permanent grassland sward was determined. The sward composition differed between different parts of the hillslope, and relative abundance of sown species was 16.5, 27.9 and 28.3% respectively, for the summit, midslope and footslope. There was a good growth of *Festuca rubra* on all parts of the hill, but *Trifolium repens* had disappeared from the grassland of the midslope and footslope. The species that disappeared were replaced by more resistant ones and some new species. There was a trend for slightly greater sward production in the footslope of the hill, and lowest in the midslope area.

**Keywords:** hilly terrain, abandoned meadow, floristic composition, dry matter yield

## Introduction

The importance of grasslands is closely linked to biodiversity, soil health and erosion control (Lange *et al*., 2015, Bengtsson *et al*., 2019). Changes in plant diversity reflect the environmental conditions (pedo-climate) and management practices (mowing, fertilization, grazing, etc.) (da Silveira Pontes *et al*., 2015). In Lithuania, about 19% of agricultural land areas are eroded and in the Zemaiciai Highland this is 35%. Under the conditions of hilly relief, plants germinate, grow and develop unequally (Monstvilaitė and Kinderienė, 2000). Abandoned grasslands lose biological diversity and their economically valuable use as a source of forage. It is important to know which plant species spread in abandoned grasslands and what are the perspectives of their use. The objective of the present study was to estimate the changes in phytocenoses' floristic composition in different parts of the hill.

## Materials and methods

The experiment was carried out at the Vezaiciai Branch of the Lithuanian Research Centre for Agriculture and Forestry on the hilly topography of Zemaiciai Highland (latitude 55°577' N, longitude 22°482' E, 185.0 m above sea level). This study analyses long-term monitoring data of a soil erosion experiment set up on slopes of 9-11º steepness. The soil of the south-facing slope was a slightly eroded Eutric Retisol. The climate of the study area is transitional between a maritime climate and a continental climate. The mean annual precipitation is 816 mm, with a maximum monthly rainfall of about 90 mm in August. The mean annual air temperature in the region is 6.3 °C, ranging from -3.4 °C in January and February to 17 °C in July. In 1993, to protect the hill from erosion, a grass-legume mixture (*Phleum pratense* L. 20%, *Festuca rubra* L. 20%, *Poa pratensis* L. 20%, *Trifolium repens* L. 20%, and *Lotus corniculatus* L. 20%) was sown in different parts of the hill (summit, midslope, footslope). The grassland has not been fertilized or used. Table 1 shows soil properties.

For plant sampling stationary 21 $m^2$ square plots of 7×3 m have been arranged in each part of the hill. Each model plot was split into 3 rectangular replicates (7×1 m) 7 $m^2$. Thirty samples of herbage were taken from every model plot and analysed. The location of samples in a model plot was chosen randomly. The experimental area was cut twice in 2020 (mid-June and end of July). Dry matter (DM) yield was measured at each harvest in fixed areas of 0.25 $m^2$ in four positions for every plot. Botanical composition of the sward was determined before the first cut.

Table 1. Agrochemical and physical properties of the soil (0–15 cm) in 2020. Mean values ± standard error. The average soil moisture was determined during plant growing season.

| Soil properties | Parts of the hill | | | Methods |
|---|---|---|---|---|
| | Summit | Midslope | Footslope | |
| Soil $pH_{KCl}$ | 5.6±0.20 | 6.2±0.16 | 5.0±0.05 | Potentiometric method |
| Total N, % | 0.114±0.00 | 0.137±0.01 | 0.132±0.00 | Kjeldahl method |
| Mobile P mg $kg^{-1}$ | 20.3±2.96 | 31.0±9.24 | 11.3±2.05 | Egner-Riehm-Domingo (A-L) |
| Mobile K mg $kg^{-1}$ | 162.7±15.6 | 158.9±21.3 | 200.9±17.00 | Egner-Riehm-Domingo (A-L) |
| Soil moisture, % | 22.4±3.2 | 22.2±1.6 | 27.2±5.9 | Weight method |

The index of relative abundance of species (P%) expressed in percent was used in this work (Peeters, 1989). The formula is as follows: $P\% = \frac{F\%}{\sum F\%} \times 100$,

where *F%* is the frequency of occurrence of every species: $F\% = \frac{n}{N} \times 100$,

where *n* is the number of samples, in which species were found; *N* is the total number of samples in a model plot; $\sum F\%$ is the sum of frequencies of occurrence of all the plant species in a model plot. Statistical analysis of DM yield data was carried out using ANOVA.

## Results and discussion

Diverse competition of different plant species stimulated spontaneous naturalization processes in the grassland. In total, in sown permanent grassland we identified 42 vascular plants species belonging to 15 families. *Asteraceae* (10 species) and *Poaceae* (8 species) were the dominant plant families. The greatest number of species were found at the summit area of the hill. Relative abundance of sown species was 16.5, 27.9 and 28.3% respectively, in the summit, midslope and footslope of the hill. *Festuca rubra* was the phytocenose-forming dominant species in the midslope and footslope, but it remained in all parts of the hill (P% = 15.1, 23.0 and 20.6, respectively, in the summit, midslope and footslope of the hill) (Table 2).

Table 2. The yield (Mg $ha^{-1}$ $yr^{-1}$) and phytocenoses' floristic composition in different parts of the hill. LSD: least significant difference. F%: frequency of occurrence of every species P%: relative abundance of species.

| | Summit | | Midslope | | Footslope | |
|---|---|---|---|---|---|---|
| Number of species | 29 | | 24 | | 25 | |
| Yield: 1st cut / 2nd cut. $LSD_{05}$ 1.704 / 0.716 | 2.00 / 1.83 | | 1.08 / 2.07 | | 2.06 / 2.01 | |
| | F% | P% | F% | P% | F% | P% |
| *Festuca rubra* [1] | 66.7 | 15.1 | 93.3 | 23.0 | 96.7 | 20.6 |
| *Phleum pratense* [1] | - | - | 13.3 | 3.3 | 6.7 | 1.4 |
| *Poa pratensis* [1] | - | - | 3.3 | 0.8 | 6.7 | 1.4 |
| *Agrostis stolonifera* | 13.6 | 2.9 | 3.3 | 0.8 | 10.0 | 2.1 |
| *Alopecurus pratensis* | - | - | 3.3 | 0.8 | - | - |
| *Dactylis glomerate* | 43.3 | 9.4 | 26.7 | 6.5 | 60.0 | 12.7 |
| *Elytrigia repens* | 43.3 | 9.4 | 70.0 | 17.1 | 23.3 | 4.9 |
| *Festuca pratensis* | 36.7 | 8.0 | 3.3 | 0.8 | - | - |
| *Festuca ovina* | 3.3 | 0.7 | - | - | - | - |
| Total *Poaceae* | | 45.5 | | 53.1 | | 43.1 |
| *Lotus corniculatus* [1] | 3.3 | 0.7 | 3.3 | 0.8 | 23.3 | 4.9 |
| *Trifolium repens*[1] | 3.3 | 0.7 | - | - | - | - |
| *Vicia cracca* | 66.7 | 14.5 | 20.0 | 4.5 | 80.0 | 16.9 |
| *Vicia sepium* | - | - | 16.7 | 4.1 | 26.7 | 5.6 |
| Total *Fabaceae* | | 15.9 | | 9.4 | | 27.4 |
| Total other species | | 38.6 | | 37.5 | | 29.5 |
| Low agronomic value plants | | 26.7 | | 31.0 | | 12.6 |

[1] sown species

*Lotus corniculatus* is intolerant of shading and therefore could not compete well with *Poaceae* species and was grown over (P% = 0.7, 0.8 and 4.9, respectively, for the summit, midslope and footslope of the hill). A small amount of *Lotus corniculatus* was found in the summit and midslope of the hill, its frequency was greatest in the footslope with more moist soil. *Trifolium repens* disappeared from the grassland of the midslope and footslope, and *Poa pratensis* and *Phleum pratense* disappeared from the grassland of the summit. Relative abundance of low agronomic value species (*Elytrigia repens, Cirsium arvense*, *Equisetum arvense*, *Rumex crispus*) was 26.7, 31.0 and 12.6% respectively, in the summit, midslope and footslope of the hill. DM yields of the first and the second cut of abandoned grassland was poor (3.15-4.07 Mg $ha^{-1}$ $yr^{-1}$). In the footslope of the hill, with more favourable environment and nutrition conditions for plants (Table 1), the yield was determined to be greater by 6.3-29.2% compared to other parts of the hill, but the differences were not significant (Table 2).

## Conclusions

The different parts of the hill (summit, midslope and footslope) showed different effects on the floristic composition of the meadow, indicating that naturalization processes affected different areas of the slope unequally. Due to better soil nutrient status and moisture conditions the meadow was more productive in the footslope of the hill, and was the least productive in the midslope of the hill. Plant species of low agronomic value (*Elytrigia repens, Cirsium arvense*, *Equisetum arvense*, *Rumex crispus*) were increasingly becoming established in the summit and midslope areas of the hill, indicated the beginning of sward degradation.

## Acknowledgements

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# Initial evaluation of PlanetScope nanosatellite images applicability for identification of grazed plant communities

Radkowski A.[1], Radkowska I.[2], Drzewiecki W.[3], Pirowski T.[3] and Szewczyk W.[1]

*[1]Department of Agroecology and Plant Production, University of Agriculture in Kraków, Mickiewicza 21, 31-120 Kraków, Poland; [2]Department of Cattle Breeding, National Research Institute of Animal Production, Krakowska 1, 32-083 Balice, Poland; [3]Department of Photogrammetry, Remote Sensing of Environment and Spatial Engineering, AGH University, Al. Mickiewicza 30, 30-059, Krakow, Poland*

## Abstract

The aim of the research was to assess the possibility of using nanosatellite images to identify chosen plant communities in the areas of pastures grazed by Hutsul horses. The surface cover is dominated by grasses, and the species composition includes herb and weed communities. Plant communities were mapped in the field using the Braun-Blanquet approach and then matched with the PlanetScope nanosatellite images. In particular, for mapped communities we created the temporal profiles of selected vegetation indices. The obtained results are encouraging, showing possible use high-resolution satellite imagery as a tool to support more effective management of grazed areas.

**Keywords:** grazing, multispecies sward, high-resolution satellite images, vegetation indices

## Introduction

Grazing animals provide the best way for utilizing permanent grassland. Pastures are characterized by having a rich flora and fauna, and therefore are of great importance in maintaining biodiversity in agricultural areas. Apart from the production importance, grasslands fulfil numerous ecological functions in the natural environment. The subject of the research reported here is the analysis of the occurrence of diverse plant communities in the selected area of the Low Beskids, near the border with Slovakia. The actual vegetation, which is the result of grazing by Hutsul horses, is presented. This area is floristically complex and for this reason we wanted to answer the question of whether the data from the PlanetScope Dove satellite are useful for fast and effective detection of variation and changes in plant cover.

## Materials and methods

Plant communities were mapped in the field during the 2018 vegetation season. The study covered an extensively used pasture with an area of 111 ha. Larger areas of undesirable plants as well as desirable grazed communities were mapped using GPS and aerial orthophotomap. In our research we used the PlanetScope Dove nanosatellite images. PlanetScope satellite constellation offers daily acquisition of high-resolution multispectral images. Newly deployed sensors have five spectral channels. However, for time period adopted in this study, defined as 1 April till 31 October 2018, only 4-channel images (blue - B, green - G, red - R, near-infrared - NIR) were available. We used cloud-free atmospherically corrected satellite ortho images with spatial resolution of 3.125 m. Plot size ranged from 0.12 a to 3.97 ha. The images were acquired using Planet API (Planet Team, 2017).

For mapped communities we created the temporal profiles of several vegetation indices reported as useful in other studies of grasslands Lin *et al*., 2019; Pasqualotto *et al*., 2019).

For every image we calculated:

- Near-infrared Reflectance of Terrestial Vegetation (NIRv) defined as (NIR-R)/(NIR+R) * NIR (Badgley *et al*., 2017),
- Green Chlorophyll Index (CIg) defined as (NIR/G)-1 (Gitelson *et al*., 2003),
- Chlorophyll Vegetation Index (CVI) defined as (NIR/G)*(R/G) (Vincini *et al*., 2008).

Based on indices images we created temporal profiles. The means of index values for each date were calculated based on pixels within areas mapped as covered by particular community. Pixels situated

closer than 5 m from the shape border were excluded from calculations. The numbers of pixels (3.125 x 3.125 m) used for averaging the values of remote sensing indices for mapped communities were: *Calamagrostis epigeios* – 26, *Prunus spinosa* – 587, *Menthea longifolia* – 420, *Cirsium – Carduus* – 1309, *Urtica dioica* – 75, *Rudbeckia lanciniata* - 12, *Petasitetum kablikiani* – 21, other (desirable grazed communities) – 4071. The simply distance-based separability measure, M-statistic (Swain and Davis, 1978), was used to evaluate possible separability between plant communities.

## Results and discussion

Based on created temporal profiles of vegetation indices (Figures 1-3) we can make several observations. First, we can see that *Calamagrostis epigeios* differs from other communities in the case of NIRv and gives the lowest values for almost entire growing season. The only exception is the image from 4 August when lower values were observed for *Rudbeckia lanciniata* and *Cirsium – Carduus* as a possible cumulative effect of grazing, nursing mowing of leftovers and drought (it is worth noting that these two communities have very similar courses of temporal profiles of every investigated index).

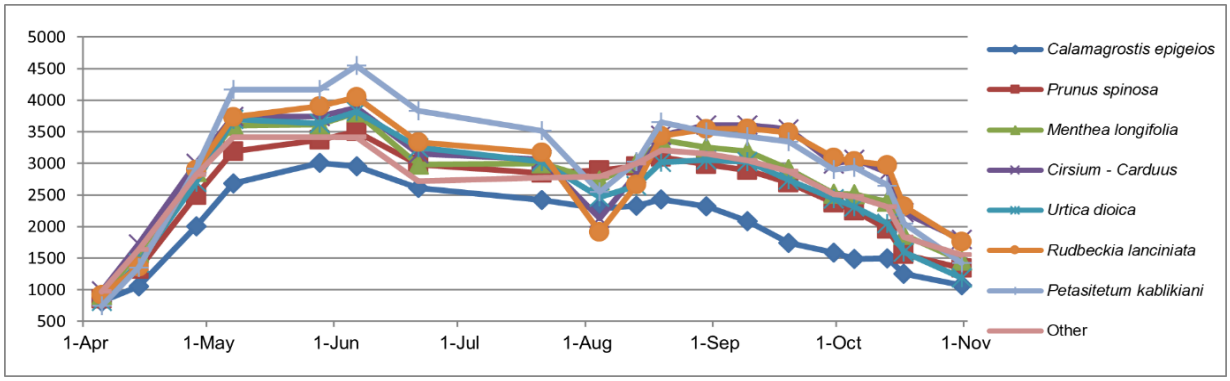


Figure 1. Temporal profile of NIRv values.

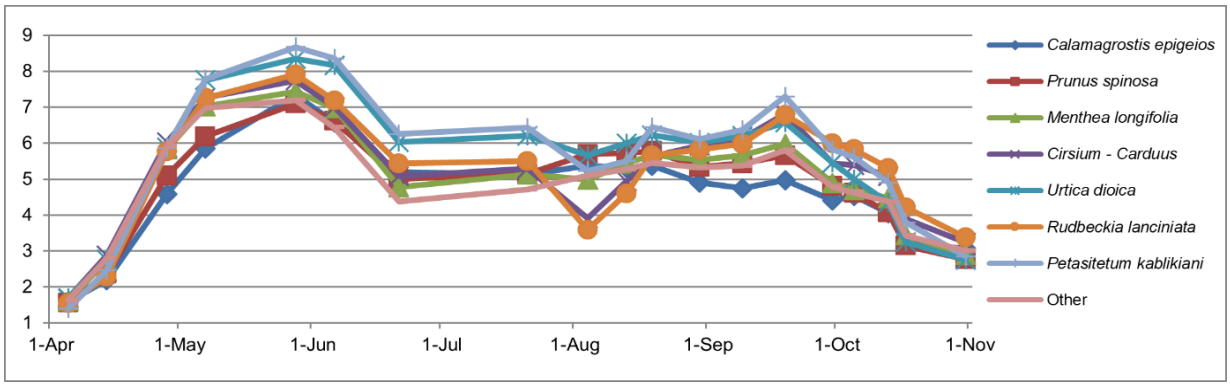


Figure 2. Temporal profile of CIg values.

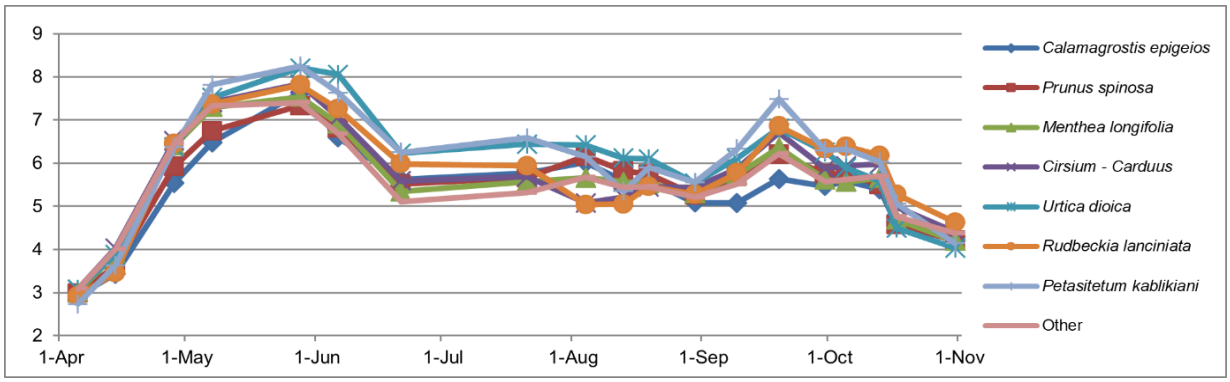


Figure 3. Temporal profile of CVI values.

Secondly, the NIRv values of *Petasitetum kablikiani* are the highest ones for May, June and July. The same is observed for CIg and CVI indices; however *Urtica dioica* profiles also show a similar course. A third important observation is that for the remaining considered indices in June and July the profiles of desirable grazed plants are distinguishable from the undesirable ones. Their values are lower than values averaged for mapped undesirable plants.

## Conclusions

Based on this preliminary study we assume that it is possible to use high-resolution satellite imagery as the support for more effective management of grazed areas. In our opinion, the reported study shows there is potential for PlanetScope Dove images for use in mapping desirable and undesirable plant communities within grazed areas. As the next step of our research we plan to evaluate the accuracy of automating classification done for such purpose.

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# Wide-area monitoring of soil moisture in peatlands using Sentinel-1 images

Yang C-H.[1], Mader S.[1], Müller S.[1], Haub C.[1], Müterthies A.[1] and Herrmann A.[2]

*[1]EFTAS Fernerkundung Technologietransfer GmbH, Germany; [2]Humboldt-Universität zu Berlin, Germany*

## Abstract

Peatland functions as an essential ecosystem that stores carbon and prevents flooding by retaining water. Monitoring of peatlands, based on remote sensing, assists in the ecological service provision for grassland and agricultural use. Soil moisture plays an important role during the hydrological cycle, and EFTAS has developed a novel approach using multi-temporal Sentinel-1 images to evaluate, model, and predict the soil moisture. Our initial test in a peatland shows promising results. The Pearson correlation coefficient between the soil moisture estimated by our model and the in-situ data is up to 0.93. We have created forward models to predict soil moisture. The lowest absolute mean error is 3.63% (volumetric water content). This work is part of the interdisciplinary research project BEWAMO funded by German Federal Ministry of Food and Agriculture.

**Keywords:** soil moisture, advanced DInSAR, time-series analysis, Sentinel-1, peatland

## Introduction

German peatlands are widely used as grasslands. Due to intensive drainage for agricultural purposes the former waterlogged peat layer has decomposed by aerobic microorganisms, resulting in enhanced emissions of greenhouse gases (Tiemeyer *et al.*, 2016). Drainage has also lead to subsidence processes of the peat layer to a point where a site is no longer classified as peatland. It is not only the observation of long-term subsidence of the peat layer that is important in monitoring peatlands; oscillations within the peat layer may also occur over the year due to shrinkage and swelling processes as a result of water loss and replenishment during the drier and wetter seasons. Imaging RADAR from Sentinel-1 constellation satellites can be used to monitor these movements and their spatial distribution on short time scales based on repeated distance measurements. Statistical analysis shows that these short-term fluctuations in thickness are significant and strongly related to soil moisture in the peat layer.

## Materials and methods

Our forward model is built via regression to evaluate soil moistures from SBAS-derived movements near the ground surface (Figure 1).

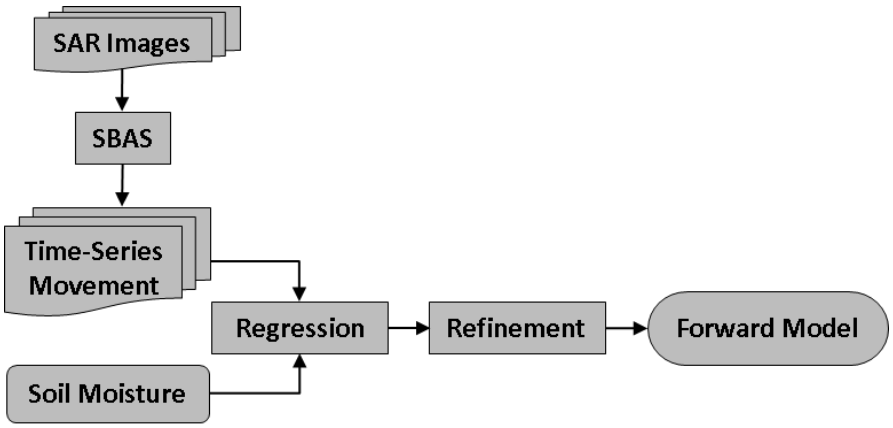


Figure 1. Forward model by regressing soil moisture on time-series movement derived from Sentinel-1 images by SBAS (Berardino *et al*., 2002).

The soil moisture in 5 cm is measured as volumetric water content (%) each day every 6 hours by a Decagon 5TM sensor. Here we used only the data measured at 6 pm, close to the acquisition times of the Sentinel-1 images. We estimated the surface movement from Sentinel-1 images via SBAS

(Berardino *et al*., 2002). The forward model will be refined after the first regression. Some inputs, i.e., pairs of movements and moisture readings, are thus removed in the second regression if their residual errors exceed a certain tolerance. This step will be iterated until all the residual errors are below the defined threshold. Finally, a forward model is generated for local use.

Our test site is a grassland located in the Rhinluch area around 50 km northwest of Berlin. This area is characterized by a homogeneous vegetation cover, soil type, and water content. Sensors were installed by the Division of Soil and Site Science at Humboldt-Universität zu Berlin to measure the soil moisture each day every 6 hours from mid-November 2019 to mid-May 2020.

## Results and discussion

Our approach implemented SBAS processing to compute the surface movement of the test areas. Here only the VV-polarized Sentinel-1 images were used. The resultant cumulative movement series along line of sight are averaged within the test grassland (Figure 2). The PCC to the measured soil moistures is 0.91, which is sufficiently high to validate the core assumption in our modelling. We predicted the soil moistures via the forward model (Figure 2). The mean absolute error to the ground truth data is 3.15% during the measurement period of 6 months. Overall, we believe our modelling is ready for local end use, at least for those sites similar to ours, i.e., low vegetation cover plus organic soils. We will adapt our approach for different site conditions, e.g., dense vegetation cover or inorganic soil body. Under these conditions the soil moisture data might not be captured in a way we have assumed.

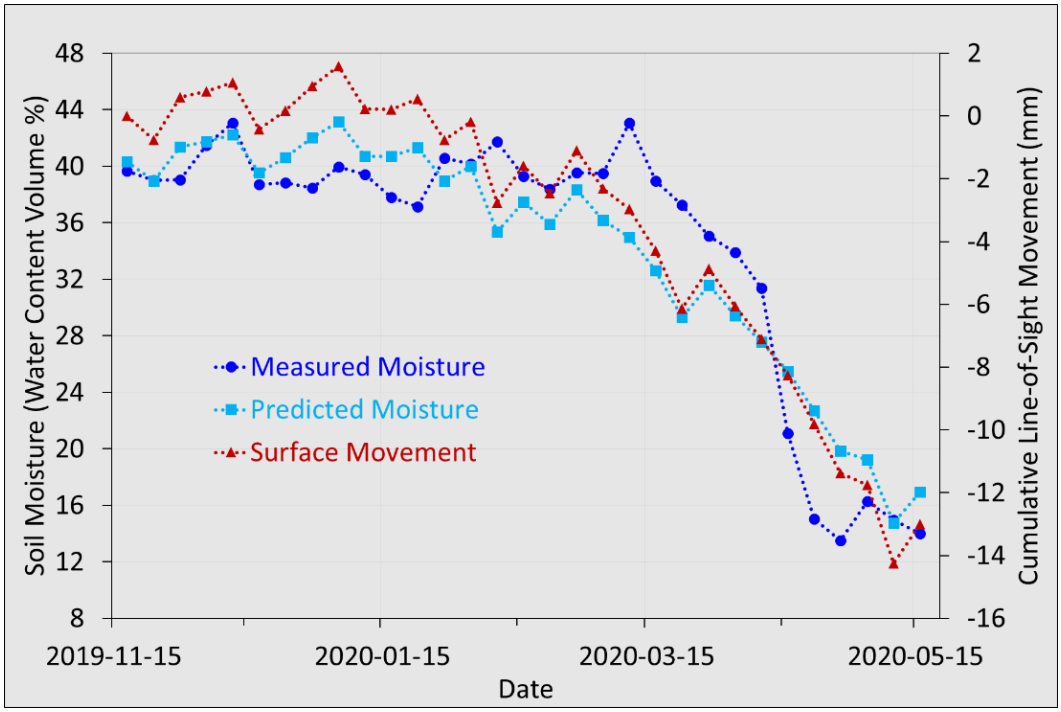


Figure 2. Comparison of soil moisture and SBAS-derived movement at test site. Movement: negative and positive, away and towards Sentinel-1 antenna (Berardino *et al*., 2002). Sample dates correspond to Sentinel-1 acquisitions.

## Conclusions

Our novel approach is able to evaluate the time-series soil moisture of a certain region from multi-temporal spaceborne SAR images. We have tested it using Sentinel-1 images in the grassland of organic soil within State of Brandenburg, Germany for a 6-month period. The PCC between the measured soil moistures and the DInSAR-derived movements is 0.91. The soil moisture values predicted from the forward models were compared with the measurements. The mean absolute error (volumetric water content %) is 3.15%. The absolute accuracy is relevant considering that the actual moistures dropped by around 30% in 6 months. Overall, we believe our modelling is ready for local end use, at least for those sites featuring low vegetation cover plus organic soils.

## Acknowledgements

We appreciate the free access to the data used in this study. The Sentinel-1 images are provided by Copernicus - European Union's Earth Observation Programme. The precipitation and temperature were downloaded from Deutscher Wetterdienst. We also want to thank our partners within the BEWAMO Project (funded by the German Federal Ministry of Food and Agriculture under Grant no. 281B301416.) for the provision of measurement data and technical discussion.

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# European Monitoring of Biodiversity in Agricultural Landscapes (EMBAL)

Lindemann D.[1], Oppermann R.[2], Sutcliffe L.[2], Moser D.[3] and Haub C.[1]

*[1]EFTAS Fernerkundung Technologietransfer GmbH, Oststraße 2-18, D-48145 Münster; [2]Institute for Agroecology and Biodiversity (IFAB), Böcklinstraße 27, D-68163 Mannheim; [3]Environment Agency Austria (EAA), Spittelauer Lände 5, A-1090 Wien*

## Abstract

The 'European Monitoring of Biodiversity in Agricultural Landscapes' project (EMBAL) is an initiative launched by the European Commission (DG Environment) which aims to provide a harmonized pan-European overview about the state and changes of biodiversity in agricultural landscapes. On the basis of the first EMBAL study (Oppermann *et al.*, 2018) and its preceding project LISA (Oppermann *et al.*, 2021) a recent contract has been assigned between 12/2019 and 10/2021 in order to consolidate and operationalize the achieved survey methodology, while proving its practical feasibility and statistical efficiency via dedicated pilot surveys on 250 sites across four bio-geographic regions within the EU. With the consolidation of the methodology and the technical workflow, this pilot project prepares the emphasized EMBAL rollout in the EU, aiming to contribute to a number of EU environmental policies (e.g. EU Biodiversity Strategy for 2030, EU Common Agricultural Policy, EU Pollinators Initiative) and to monitor their implementation and effectiveness.

**Keywords:** biodiversity, agriculture, EU, landscape, monitoring

## Introduction

European agricultural and environmental policies are increasingly challenged with providing sufficient results in terms of maintaining and enhancing biodiversity, especially in agricultural landscapes. Agricultural policy is the biggest policy sector in the EU and the greatest decline in biodiversity has been in agricultural landscapes (e.g. compared to forests and settlements). However, until now a European-wide monitoring approach for the ecological quality of agricultural landscapes is missing. Therefore, the EMBAL approach has been developed and its aim is to fill the gap between very detailed but small-scale information on biodiversity on the one hand side, and robust but meaningful harmonized information on farmland biodiversity and its change at a large scale on the other hand.

## Materials and methods (Description of the EMBAL approach)

For each EU member state a significant number of EMBAL plots needs to be investigated in the field in a regular perennial repetition rate. It is based on a three-survey level (see Figure 1):

1. EMBAL plot (500 x 500 m)

Recording unit with 500 x 500 m edge length (25 ha), arranged in a regular grid of 2 x 2 km across the EU-27 Member States, based on the LUCAS master sample grid (Eurostat 2019).

2. Parcels and landscape elements

Within each EMBAL plot, all agricultural parcels and linear landscape elements are delineated and described by recording a basic set of parameters, such as land cover and land use, number and colours of flowering forbs, coverage of crop and wild plants on arable land or vigour and graminoid-forb ratio on grassland.

3. Vegetation transects

Each plot contains up to 9 vegetation transects, whose position is determined by 5 regularly arranged identification points. Vegetation transects are 20 m in length and 2.5 m wide and surveyed in pairs – one at the field margin, and one in the field interior. They are only observed in either grassland or cropland. Here, more detailed parameters, such as the presence of plant indicator species (key species), different vegetation layers or number of flowering forbs and their density will be recorded (Oppermann *et al.*, 2017).

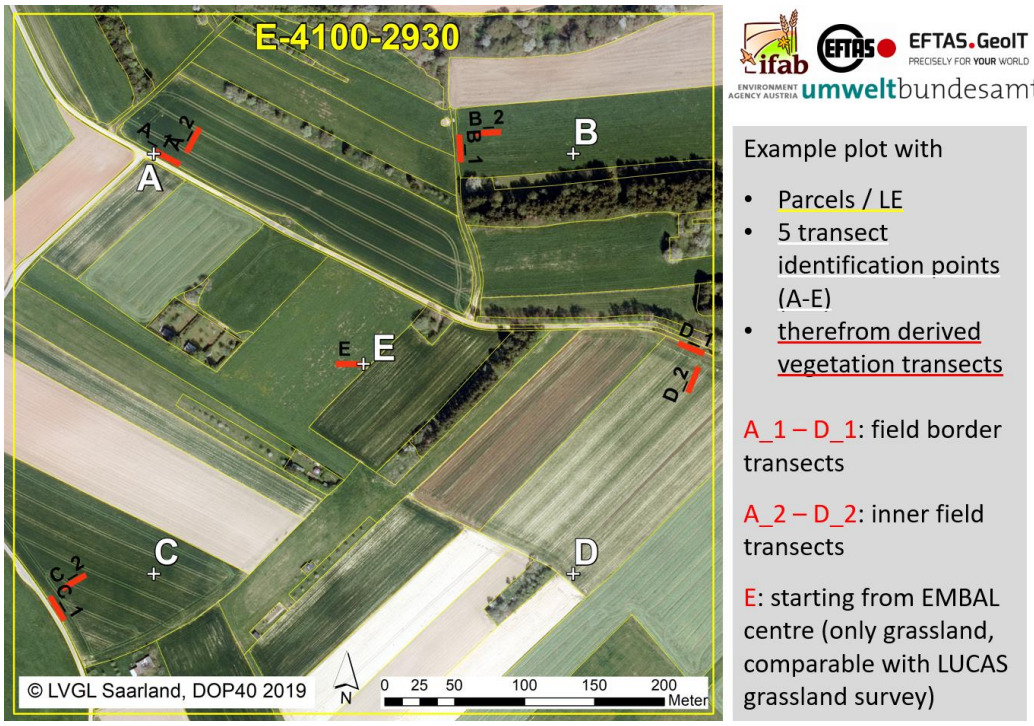


Figure 1. Example of an EMBAL plot (Location: Aschbach, Saarland [NUTS1], DE)

## Results (Implementation of the EMBAL pilot study)

The technical implementation of this project addresses four technical aspects. The *first task* is the methodological review and consolidation of the achieved survey approach, while exploring synergies with other European initiatives such as the Land Use / Cover Area Frame Survey (LUCAS) (Eurostat 2019) and satellite earth observation-based services as from the EU Copernicus framework (EEA 2021). The *second task* is to establish a digital data collection workflow by means of open source tools. The *third task* is the execution of pilot surveys across four biogeographic regions. The *fourth task* is to assess statistical efficiency and demonstrate the added value of EMBAL information by means of selected use cases.

From these technical specifications, the following should be highlighted:

1. All parameters from EMBAL 2017 have been thoroughly evaluated and enhanced. The pollination potential is taken into account through the assessment of flowering species, their density and their distribution. Emphasis is also put on synergy effects with the established statistical field survey LUCAS (Eurostat, 2019). Here EMBAL makes use of the LUCAS 2 x 2 km master grid and considers the comparability of parameters such as land cover in general, and in particular in relation to the new LUCAS Grassland module 2018.

2. The EMBAL method and approach are tested and validated in pilot surveys in 2020 (DE) and 2021 (ES, RO & AT) on 250 plots, and provide results from 4 different biogeographical regions and diverse agricultural cultivation forms and intensities across the EU.

3. EMBAL is faced with great challenges in terms of technical preparation, implementation in the field and the preparation and consolidation of tabular and spatial data after survey. Therefore, a digital workflow was developed, which takes into account the complexity required, and is based on open source components (Kobs and Kleinewillinghöfer, 2020).

4. Evaluations of statistical significance regarding changes in biodiversity parameters and comparisons between regions are ongoing, as well as the calculation of statistically robust sample sizes (power analyses) for plots and transects. They form the basis for the calculation of a sample of a later EU-wide rollout (Moser, 2020).

5. External expert consultation is essential for future applicability of EMBAL. For this reason, two expert workshops take place, of which the first was already implemented with participants from various EU and non-EU institutions, which are closely related to the fields of environmental monitoring and remote sensing (Haub *et al.,* 2021).

## Outlook

During the period of the EMBAL pilot study the second workshop is scheduled for 6 May 2021. Its aim is to consult with relevant authorities from the EU Member States regarding the enhanced and future applications of the EMBAL methodology.

An outlook for opportunities and recommendations for an expansion of EMBAL to a Pan-European long-term monitoring system will be provided to derive spatially extensive information about the biodiversity of agricultural landscapes within Europe. Results of a double blind between non-botanical experts and botanists will be presented at the conference.

Different scenarios for a sampling design of EMBAL will be identified in order to use it as input and validation data to derive remote sensing products from Copernicus satellite data, and to assess the added value to use the EMBAL field data in combination with the LUCAS dataset to derive valuable information for the implementation of EU Pollinators Initiative and the Green Infrastructure strategy.

## Conclusions

The interim results indicate that EMBAL will be a unique and powerful tool to monitor biodiversity in European agricultural landscapes and particularly to evaluate how far and if European legislations and measures to preserve and regenerate the natural resources and nature capital are effective.

With the recorded species groups, additional environmental and structural parameters, and the different spatial components of EMBAL, it becomes possible to generate objective information for nature value and biodiversity to evaluate the impact of agri-environmental policies, since there are no comparable data for this at EU level to date.

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# Lifting the secrets of pastures: Overview of animal-borne sensors to uncover processes unobserved by classical grassland research

Pauler C. M. and Schneider M. K.

*Forage Production and Grassland Systems, Agroscope, Zurich, Switzerland*

## Abstract

Movement and foraging behaviour of grazing livestock strongly respond to pasture vegetation while being major drivers of grassland biodiversity. However, many underlying processes of these interactions are scarcely understood. In this article we focus on how animal-borne sensors can close this knowledge gap. We conducted three grazing experiments on heterogeneous pastures in the Swiss Alps. GPS-trackers, pedometers, nose-band chewing sensors and head-collar accelerometers were fitted to cattle, sheep and goats. Sensor data were combined with classical vegetation surveys. We found that (1) animal-borne sensors allow for monitoring activities of grazing animals continuously, objectively and without disturbing their natural behaviour; (2) sensors can monitor processes not directly observable by humans or aerial systems but sensed by livestock; (3) the high temporal and spatial resolutions allow for new algorithms of data interpretation. Combining these advantages of animal-borne sensors with classical measurements revealed novel ecological relationships of livestock behaviour and vegetation diversity. For instance, we disentangled interactions of cattle movement behaviour, their spatial distribution, anatomy, trampling pressure, plant trampling-adaptation and pasture vegetation and diversity. Animal-borne sensors indicate the underlying ecological processes of pasture parameters and not only their status quo, and thereby enable a holistic research approach into grassland systems.

**Keywords:** animal-borne sensors, GPS, pedometer, chewing sensors, herbivore-pasture interaction

## Introduction

Modern sensing technology observes numerous processes in grassland. However, for pastures there is a lack of information, as they are not only influenced by climatic, edaphic and topographic factors but also substantially by herbivores. Grazers shape pasture vegetation and biodiversity by selective defoliation, trampling, nutrient translocation and even seed dispersal (Pauler *et al*., 2019). Inversely, pasture forage quality, plant species composition and terrain influence animal behaviour. Common grassland sensing methods focus on the vegetation site of these fundamental interactions and thus, important ecological relationships are often overlooked in pasture sensing. Applying animal-borne sensors, the animal itself provides in-situ insights in the ecosystems parameters. Many ecological processes and relationships are not detectable without the animal – especially on heterogeneous pastures. However, the use of animal-borne sensors requires a thorough handling and interpretation to achieve meaningful results. This article demonstrates that animal-borne sensors are a valuable addition to classical grassland research focusing on vegetation parameters. We discuss opportunities and challenges encountered in several field studies.

## Materials and methods

We refer primarily to three field experiments conducted on heterogeneous, (sub-)alpine pastures in the Swiss Alps (Homburger *et al*., 2015, 2014; Pauler *et al*., 2020a, 2020b) (plus a third study not yet published). Grazing behaviour of cattle, sheep and goats was observed applying various sensors (Table 1). Sensor data were combined with vegetation surveys, chemical analysis of soil and forage, other grassland sensing methods (e.g., calculating vegetation height based on drone pictures) and anatomical measurements (e.g., weight, claw size). Behavioural states in space and time were classified automatically. The accuracy of both sensor output and classification was validated against visual observations in the field.

## Results and discussion

In our studies, animal-borne sensors disentangled numerous ecological relationships of livestock behaviour and vegetation diversity (Table 1). For instance, using GPS and pedometers we were able to identify drivers of animals' spatial distribution and movement intensity (Homburger *et al*., 2015; Pauler

*et al*., 2020a). The movement behaviour was influenced by terrain (e.g., avoidance of steep slopes) as well as the forage on offer (e.g., preference of nutrient-rich areas; fewer steps in high forage quality paddocks). However, the herbivore-grassland relationship is reciprocal: by combining sensor data with vegetation surveys, we found that plant species richness and the proportion of trampling-adapted species are influenced by the movement and foraging behaviour of animals (Pauler *et al*., 2019). Combining different sensing methods and classical surveys enlarges the knowledge gain considerably.

Table 1. Overview of pasture-relevant, animal-borne sensors, their output, the challenges to be considered and the ecological questions that can be answered by interpreting sensor output. All sensors provide temporal assignment and thus allow integration of different devices.

| Sensor | Output | Challenges | Interpretation | Underlying process |
|---|---|---|---|---|
| GPS logger | Position | Insufficient accuracy due to shading;<br>Insufficient robustness;<br>High energy demand | Distance covered;<br>Spatial distribution;<br>Activity classification: resting, foraging, walking | Location of defoliation and nutrient deposition |
| Pedometer | Step frequency + intensity | Black-box data;<br>Comparable only for animals of similar size | Movement intensity;<br>Activity classification: lying, walking | Biomass and soil compaction |
| Nose-band chewing sensor | Bite rate + intensity;<br>Rumination | Automated classification difficult or relying on black-box software;<br>Error-prone at low temperatures | Activity classification: foraging, rumination | Amount of defoliation |
| Head-collar accelerometer | Position of the head | Automated classification difficult or relying on black-box software | Activity classification: foraging, browsing | Structure of defoliation (herbs vs. woody) |
| Under-chin cameras* | (Motion) pictures | Difficult automated classification;<br>Identification of individual forage plant species not always possible | Activity classification: resting, foraging, browsing, rumination, walking, interaction | Selective foraging (species identity, developmental stage of forage) |

* Not applied in the studies presented, but with high potential (e.g., de la Rosa, 2019).

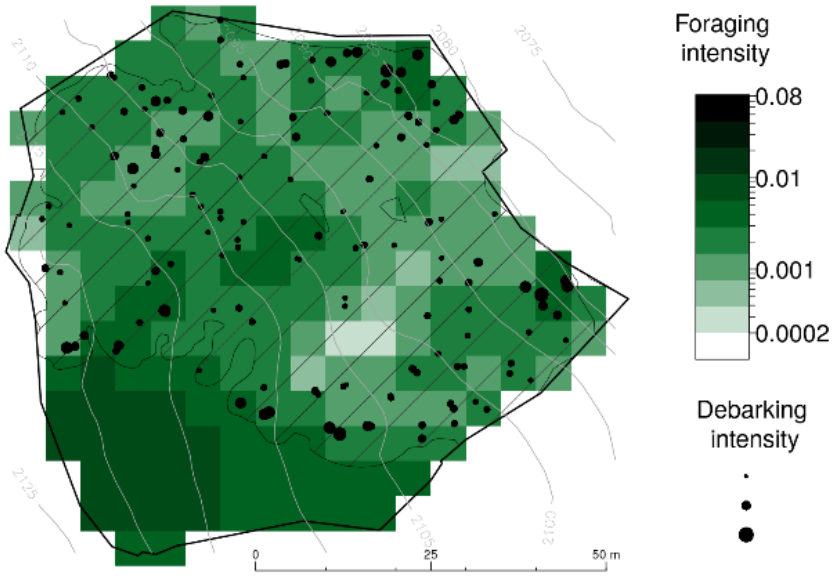


Figure 1. One example of combining classical vegetation survey and animal-borne sensors. Sheep grazed subalpine pastures partially covered by *Alnus viridis* stands (hatched). They prefer flat over steep slopes and open pasture over shrub stands, but when entering the stands, debarking intensity is a function of sheep occupancy. Debarking recreates open pastures and the more the thickets are thinned, the greater the species richness.

Another reciprocal interaction we could demonstrate was for nutrient flux: animal-borne sensors demonstrated that the spatial distribution of animals is more even during foraging than on average. Thus, animals ingest nutrients from all over the pasture, but mainly deposit them at only a few resting places, as confirmed by dung sampling (Koch *et al.*, 2018). Thus, livestock change the competitive conditions and thereby alter vegetation composition. Vegetation surveys show a high share of nitrophilous plants where animals rest. In return, the higher nutrient content affects livestock spatial distribution.

Animal-borne sensors record activities of grazing animals continuously, objectively and without disturbing the natural behaviour. Sensors can thereby monitor processes not directly observable by humans but sensed by the animal. However, meaningful results of animal-borne sensors depend on adequate handling and interpretation. Both can be challenging: (1) accurate fitting of sensors is time-consuming and error-prone, especially if sensors and halters were not developed for the species or breed of interest; (2) animal interactions and outdoor conditions can damage sensors, and since most devices were developed for in-house deployment, they need careful adaptation and testing in harsh environments; (3) assessing and validating the accuracy of data is crucial; (4) automatized behaviour classification is mandatory for large datasets but requires advanced programming skills. Alternatively, one has to rely on black-box classification of commercial software; (5) measurement uncertainty and the spatiotemporal autocorrelation of sensor data need to be accounted for in data analysis.

## Conclusions

Many parameters of interest in pasture grassland research (e.g., nutrient deposition, trampling impact, vegetation reaction) depend on herbivore-pasture interactions. Classical grassland sensing usually measures a status quo of these parameters (e.g., nutrient content, vegetation composition) and thus it focuses on only one site of a complex interaction. Combining these methods with animal-borne sensors facilitates the understanding of underlying ecological processes (e.g., nutrient intake and excretion, movement behaviour, forage selection). Thereby, animal-borne sensors enable an holistic research approach into grassland systems.

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# Springtime grazing for meadowbird conservation

Hoekstra N.J., de Wit J. and van Eekeren N.

*Louis Bolk Institute, Kosterijland 3-5, 3981 AJ Bunnik, The Netherlands*

## Abstract

European meadow bird populations are declining. In the Netherlands, particularly the black-tailed godwit and lapwing show reduced breeding success and limited chick survival because of increased predation, urbanization and agricultural intensification. In order to increase breeding success and chick survival, farmers are compensated for implementing conservation measures, including delayed first harvest until 1, 8 or 15 June. These measures help to create a period of rest with enough shelter against predators and sufficient food availability for the chicks. However, this delayed harvest results in a heavy grass crop, which limits chick mobility and feeding success, but also negatively affects forage quality and regrowth. In the current experiment we tested the effect of pre-grazing until 1 or 8 May on the yield, sward density (% cover at soil surface) and nutritive value of the grass harvested at a delayed harvest. Pre-grazing significantly reduced the average herbage dry matter (DM) yield from 7 t $ha^{-1}$ to 4.6 and 3.2 ton DM $ha^{-1}$ (1 and 8 May, respectively). The sward density after the delayed harvest was 18% higher with pre-grazing, and both the energy and protein content were higher. In conclusion, pre-grazing is a good tool to prevent some of the problems associated with delayed harvests under meadow bird conservation management.

**Keywords:** grazing, meadowbird conservation, sward density, herbage yield, nutritive value

## Introduction

European meadow bird populations are declining. In the Netherlands, particularly the black-tailed godwit and lapwing show reduced breeding success and limited chick survival because of increased predation, urbanization and agricultural intensification. In order to increase breeding success and chick survival farmers are compensated for implementing conservation measures, including delayed first harvest until 1, 8 or 15 June. These measures help to create a period of rest with enough shelter against predators and sufficient food availability for the chicks. However, this delayed harvest often results in a heavy grass crop, which limits chick mobility and feeding success, but also negatively affects forage quality and regrowth. In order to prevent these problems, there are also conservation measures in which farmers are allowed to graze these fields until 1 or 8 May, followed by a rest period of 4 to 6 weeks. The objective of the current experiment was to assess the effect of pre-grazing until 1 or 8 May on the yield, sward density and nutritive value of the grass harvested at a delayed harvest.

## Materials and methods

In 2018 we carried out a plot experiment in which we tested the effect of delayed harvest (1, 8 or 15 June) without grazing (NG) or with grazing until 1 or 8 May (G-1/5, G-8/5), resulting in 8 treatments (see Figure 1). The experiment was conducted in a perennial ryegrass-dominated sward at the Knowledge Transfer Centre Zegveld, which is situated on drained peat soil. The plots were 3 x 7 m and placed within a grazing trial (5 LU / ha) in 8 replicate blocks. All plots received 25 $m^3$ cattle slurry at the end of March. Additionally, after the first cut the plots received 155 kg N/ha in the form of calcium ammonium nitrate divided over 3 cuts. During each of the four cuts the dry matter yield (DMY) and nutritional value was determined by cutting the plots to 6 cm height using a Haldrup plot harvester. Grazing started on 15 April and residual sward height was on average 6.5 cm. The grass growth and dry matter during grazing was estimated based on weekly grass height measurements under 1.5 x 4 m grass cages in the grazing area adjacent to the plots. On 15 June the sward density cover at soil surface was determined using the point quadrat method (Hoekstra *et al*., 2019). ANOVA was carried out to assess the treatment effect on DMY, sward density and nutritional value.

## Results and discussion

There was a significant (*P<0.001*) treatment effect on the DMY of the first cut. The DMY without grazing ranged from 6.7 on 1 June to 7.3 t $ha^{-1}$ on 15 June (Figure 1). The grazed plots had a significantly

(*P<0.001*) lower DMY at cut 1: on average 4.6 and 3.2 t DM ha$^{-1}$ for grazing until 1 May and 8 May, respectively. This shows that grazing was an effective way to reduce the heaviness of the grass crop at delayed harvest. However, under the conditions of spring 2018, grazing until 1 May still resulted in a DMY of 4.6 t DM ha$^{-1}$, which is still very high in relation to chick mobility. This highlights the need to also minimize the fertilization rates on these fields with a relatively intensive management history.

The high herbage yields of the first cut had a negative effect on sward density and regrowth (Figure 1b). The sward density ranged from 31% (no grazing, date first cut 15 June) to 70% (G-1 May, date first cut 1 June). A delay in cutting from 1 June to 15 June resulted in a decrease in sward density of on average 30% points, whereas grazing until 1 May and 8 May (compared to NG) resulted in an increase in sward density of 10 and 18% points, respectively.

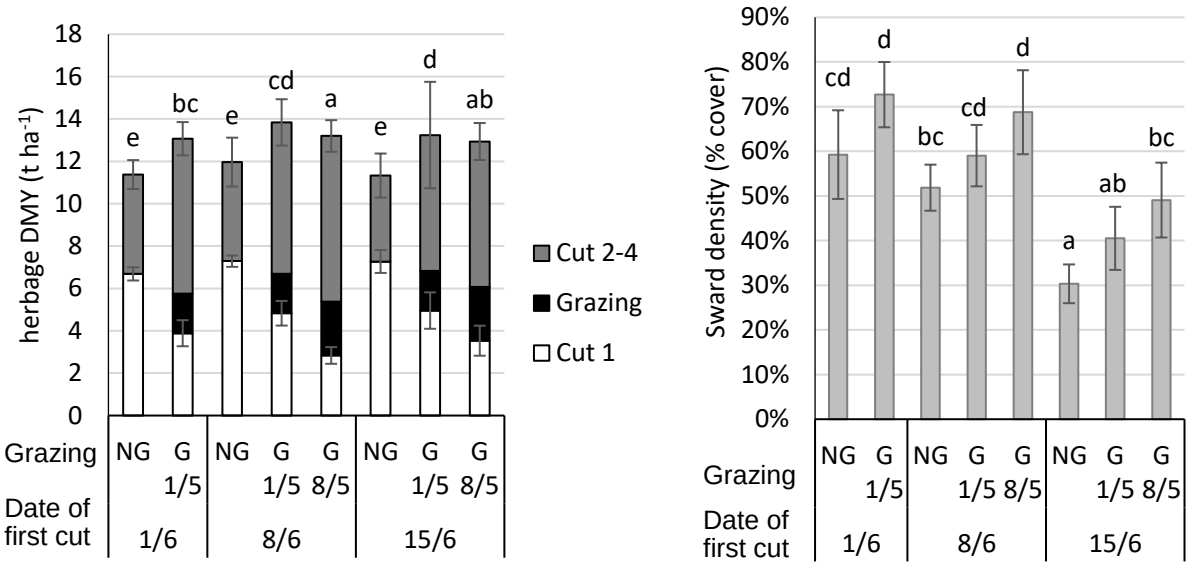


Figure 1. The effect of grazing (NG = no grazing, G 1/5 = grazing until 1 May, G 8/5 = grazing until 8 May) and cutting date of the first cut (1/6, 8/6 and 15/6) on a) the herbage dry matter yield of the first cut, and cut 2-4 and the herbage uptake during grazing and b) the sward density (% cover at soil surface) measured on 15 June. Error bars are 2×SE, n=8. Different letters above bars indicate significant differences (*P < 0.05*) in (a) the herbage DMY of Cut 1 and (b) sward density.

The DMY of the regrowth (cut 2-4, Figure 1a) was significantly higher when plots had been grazed: on average 4.5, 7.0 and 7.3 t DM ha$^{-1}$ for NG, G-1/5 and G-8/5, respectively. The cumulative herbage yield, including the estimated uptake during grazing was on average 11 t DM ha$^{-1}$ and not significantly affected by the treatments.

Table 1. The effect of grazing (NG = no grazing, G 1/5 = grazing until 1 May, G 8/5 = grazing until 8 May) and cutting date of the first cut (1/6, 8/6 and 15/6) on the energy content (VEM) and crude protein content of the herbage harvested during the first cut.

| | VEM (g kg$^{-1}$ DM) | | | Crude protein (g kg$^{-1}$ DM) | | |
|---|---|---|---|---|---|---|
| | Date of first cut | | | Date of first cut | | |
| Grazing | 1 June | 8 June | 15 June | 1 June | 8 June | 15 June |
| NG | 737 $^{b*}$ | 684 $^{a}$ | 657 $^{a}$ | 117 $^{ab}$ | 112 $^{ab}$ | 103 $^{a}$ |
| G-1/5 | 826 $^{cd}$ | 783 $^{bc}$ | 764 $^{b}$ | 143 $^{cd}$ | 130 $^{bc}$ | 125 $^{abc}$ |
| G-8/5 | | 845 $^{d}$ | 835 $^{d}$ | | 160 $^{de}$ | 147 $^{cd}$ |

Delaying the harvest date of the first cut had a strong negative effect on the energy (VEM = net energy for lactation) and protein content of the herbage harvested during the first cut. At 15 June VEM was only 657 and CP only 103 g kg$^{-1}$ DM, a reduction of -29% and -39% in comparison to the nutritional value at a regular harvest date (15 May, 927 VEM and 169 CP). This decrease in nutritional value was partly

compensated by grazing: for the delayed harvest at 15 June, VEM was 835 g $kg^{-1}$ DM and CP 147 g $kg^{-1}$ DM when plots were grazed until 8 May.

## Conclusions

Grazing was an effective way to reduce the DMY of the delayed harvest and thus possibly improve the habitat quality for meadowbird chicks, by reducing the negative impact of a heavy grass crop on chick mobility. In addition, grazing reduced the negative effects of the delayed harvest on sward density, herbage regrowth and herbage quality of the first cut. However, spring grazing by itself was not sufficient to reduce the herbage biomass in all cases, and it is also important to minimize fertilization on these fields. Care should always be taken to avoid disturbance of nests and chicks by grazing animals.

## Acknowledgements

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# Effects of innovative management options on perennial grassland in the mountain area of Switzerland

Mack G.[1], El Benni N.[1], Tindale S.[2], Hunter E.[3], Newell Price P.[4] and Frewer L.[2]

*[1]Agroscope, Socioeconomics Research Group, Tänikon, Switzerland; [2]Centre for Rural Economy, School of Natural and Environmental Sciences, Newcastle University, Newcastle upon Tyne, UK; [3]Department of Work Science, Business Economics and Environmental Psychology, Swedish University of Agricultural Sciences, Sweden; [4]ADAS Gleadthorpe, Meden Vale, Mansfield, Notts, UK*

## Abstract

Based on a Delphi study, six innovative management options were assessed with regard to their feasibility and potential effects on the delivery of ecosystem services (ES) for the Swiss alpine region: (i) complete sward renewal through sward destruction and reseeding, (ii) virtual fencing, (iii) overseeding with different grass or legume species or mixtures without complete sward destruction, (iv) practical use of rising plate meter for yield estimation, (v) biodiversity management, and (vi) weather and grass growth monitoring to improve grassland management. We found that sward renewal has negative effects on biodiversity, carbon storage, flood control, prevention of soil erosion and prevention of loss of organic matter and therefore should not be applied in the Swiss alpine regions. Rising plate meters and grass monitoring have a positive effect on grass production without any negative consequences on other ES. Biodiversity management fits perfectly under the Swiss alpine conditions, in particular when farmers are compensated for their economic loss.

**Keywords:** Delphi-study, sward manipulation, grazing management, farm-scale management, monitoring grass growth

## Introduction

Grasslands provide a wide range of ecosystem services (ES) (Bengtsson *et al*., 2019; Zhao *et al*., 2020) including provisioning services such as forage production, regulating and supporting services such as soil carbon storage, erosion control or pollination and cultural services (Huber *et al*., 2020). Climate change and changes in land use intensities affect the functioning of ecosystems and thus the delivery of ES. In the Swiss alpine regions, the delivery of ES are simultaneously affected by land abandonment (Gellrich *et al*., 2007), increasing land use intensity and climate change. Expert knowledge from researchers and practitioners is needed to develop management options that support the delivery of ES of permanent grasslands under current and changing conditions. Various innovative management options for perennial grassland have been developed, but if and how these support the delivery of ES in alpine regions is not well understood. We identified six management options that might be applicable in the alpine region (Table 1). A Delphi study was conducted to assess the feasibility and potential effects of these new management options on the delivery of ES under the specific climatic, political and institutional conditions of the Swiss alpine region.

## Materials and methods

An online Delphi study, using two rounds of questionnaires with anonymous feedback of results between rounds, was carried out with ten experts who assessed the six management options in terms of the delivery of ES and their applicability under both the current climatic conditions in the alpine region, and the socio-economic, institutional and political conditions of Switzerland. The six management options were pre-selected by experts for their representation of a range of (1) technology readiness levels; (2) level of new skills required for implementation; and (3) potential impact in the alpine region. Ten expert participants for the Delphi study were recruited from four institutions in Switzerland, representing a range of academic disciplines (economist, farm adviser, ecologist, soil scientist, livestock scientist, engineering and precision farming, veterinary scientist, animal welfare, social scientist). Experts were selected for their subject knowledge as well as contextual knowledge of Swiss alpine regions. We do not have a spatial distribution in the observations because experts were selected based only on their expertise.

A modified Delphi technique (Hasson and Keeney, 2011) was used to explore the attitudes of the interdisciplinary group of experts and gather information and opinions in order to obtain the most reliable

position of the group (Dalkey and Helmer 1963). An online survey platform was used to create two rounds of the survey. Each round consisted of closed questions, answered using likert scales, and open questions, using free text, allowing for elaboration and explanation. The first round questions focused on the assessment of each management option in relation to its rationale, mechanism of action and outcomes, ecosystem service delivery, applicability and support. The second round presented anonymized summaries of the results of the first round, highlighting agreement and disagreement, and asked participants to answer questions again for which there had been less than 80% agreement. This sought to offer experts the opportunity to clarify or change their opinions based on the answers of the other experts.

Table 1. Description of management options.

| Type | Option | Description |
|---|---|---|
| Sward manipulation | Overseeding | Overseeding is carried out on the existing sward to create establishment niches in which a selection of desired plant species can be broadcast sown or slot seeded with different grass or legume species or mixtures without complete sward destruction. |
| | Sward renewal | Complete sward renewal through sward destruction (non-selective herbicide spraying or cultivation) and reseeding; carried out when the existing sward is not meeting current land management objectives, e.g. when the current sward contains less than 50% desired species. |
| Monitoring & predicting grass growth | 'GrassCheck' | Weather and grass growth monitoring to improve grassland management and to assist farmers in improving both grass growth and utilization. It can include an online management platform to monitor and predict grass growth, grass quality and weather in different regions. |
| | Rising plate meters | Rising plate meters are used to measure grass sward height as a proxy for grass quantity. A large number of measurements can be taken in a short time so that a large area can be covered to account for spatial heterogeneity within fields. |
| Grazing management | Virtual fencing | Use of virtual fencing technologies to control and manage grazing without installing permanent barriers or the need for high labour input temporary (electric) fencing. |
| Farm-scale management | Biodiversity management | Managing grassland in a variety of ways across a farm to create a diversity of habitats and enhance biodiversity at various trophic levels from soil invertebrates to birds and mammals. |

The two rounds took place in September and October 2020, with each round's online survey open for participation during a 1.5 week period, with a break of 2 weeks in which the results of the first round were summarized for participants in the second round. Quantitative and qualitative data from the surveys were analysed using software packages SPSS and NVivo for trends and comparisons.

## Results and discussion

The majority of the experts (based on second round survey, where in total 9 experts participated) stated that four out of the six management options (overseeding, GrassCheck, rising plate meters, biodiversity management) are successfully applicable under both the current climatic conditions in the alpine region and the socio-economic, institutional and political conditions of Switzerland. Only one expert disagreed that rising plate meters are applicable in the alpine region, arguing that this option can only be implemented if the relationship between sward height and biomass is properly calibrated, a task that may be too time-consuming in the case of diverse alpine grassland regions. There was no consensus on whether sward renewal and virtual fencing are successfully applicable under the current climatic conditions of the alpine regions. One expert stated that sward renewal increases the risks of erosion and doubted that seeds adapted to the specific climatic conditions would be available. Virtual fencing is considered problematic in the alpine regions because of inaccurate georeferencing due to steep slopes.

Experts achieved a consensus that sward renewal and virtual fencing were not successfully applicable under the current political, institutional and socio-economic conditions of Switzerland. For virtual fencing, the current Swiss animal welfare legislation does not allow animals to receive electric pulses and citizens' acceptance of virtual fencing was likely to be low. For sward renewal, one expert stated that destroying swards in alpine regions was not accepted by Swiss society. However, the majority of the experts saw some potential relevance for all six management options if the climatic conditions in Swiss mountain regions were to change.

The Delphi-study showed that farm scale and sward manipulation measures such as biodiversity management, overseeding, and sward renewal affect all of the considered ES. The majority of experts stated that biodiversity management measures have a positive effect on biodiversity and pollination. Overseeding was also rated positively for biodiversity and prevention of soil erosion, while sward renewal was rated negatively for five out of nine ES (Table 2).

Table 2. Effects that each management option is likely to have on delivery of ES.

| | Biodiversity Management | Over-seeding | Sward renewal | Grass-Check | Rising plate meters | Virtual fencing |
|---|---|---|---|---|---|---|
| Biodiversity | + | + | - | +/- | +/- | n.c. |
| Pollination | + | n.c. | n.c | +/- | +/- | +/- |
| Carbon storage | +/- | n.c. | - | +/- | +/- | +/- |
| Greenhouse gas emissions | n.c. | +/- | n.c | +/- | +/- | +/- |
| Flood control | +/- | +/- | - | +/- | +/- | +/- |
| Water quality | +/- | +/- | +/- | +/- | +/- | +/- |
| Prevention of soil erosion | +/- | + | - | +/- | +/- | +/- |
| Prevention of soil compaction | +/- | +/- | n.c | +/- | +/- | n.c. |
| Prevention of loss of organic soil matter | +/- | n.c. | - | +/- | +/- | +/- |
| Landscape aesthetics | + | +/- | n.c | +/- | +/- | n.c. |
| Recreation | + | n.c. | n.c | +/- | +/- | + |
| Animal health and welfare | n.c. | +/- | +/- | + | + | n.c. |
| Grass production for livestock | - | + | + | + | + | n.c. |
| Grass production for biomass | - | + | + | + | + | +/- |

+ More than 50% of the experts stated that the management option is likely to have a positive effect; +/- More than 50 % of the experts stated that the management option is likely to have neither a positive nor a negative effect; - More than 50 % of the experts stated that the management option is likely to have a negative effect; n.c.: experts achieved no consensus.

While biodiversity management was rated positively in terms of cultural ES such as landscape aesthetics and recreation, it was rated negatively for provisioning ES such as grass production for livestock and biomass. In contrast, the majority of experts stated that both overseeding and sward renewal have a positive effect on provisioning ES. The results of the Delphi study showed that measures for monitoring or predicting grass growth such as GrassCheck and rising plate meters have neither a positive nor a negative effect on most of the ES. However, both measures were rated positively in terms of animal health and animal welfare, and for grass production for livestock and biomass. The majority of the experts considered that virtual fencing would have no effect on other than provisioning ES. While experts reached no consensus on whether it is positive or negative for animal health and animal welfare, the majority rated it positively in terms of cultural ES such as recreation.

## Conclusions and recommendations

Sward renewal should not be applied under the current climatic, political, institutional and socio-economic conditions of the Swiss alpine regions because of its foreseeable negative ecological consequences. Biodiversity management fits perfectly under the Swiss alpine conditions, in particular when farmers are compensated for their economic losses. For management options that focus on the monitoring and prediction of grass growth we found no trade-off between the different ES that could be delivered. They are recommended because of their positive impacts on provisioning services such as grass growth for livestock and biomass without any foreseeable negative consequences on biodiversity. However, virtual fencing is currently not applicable in Switzerland because of animal welfare concerns.

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# Mapping grassland management and habitats with satellite and ground level imagery through machine learning

O'Hara R.[1,2], Saad M.[2,3], Zimmermann J.[1], Green S.[1], Finn J.[4], Mac Namee B.[3], McGuinness K.[5] and O'Connor N.[5]

*[1]Teagasc, Ashtown Food Research Centre, Dublin, Ireland; [2]SFI VistaMilk Research Centre, Moorepark, Cork, Ireland; [3]UCD Insight Centre for Data Analytics, Dublin, Ireland; [4]Teagasc, Environmental Research Centre, Johnstown Castle, Wexford, Ireland; [5]DCU Insight Centre for Data Analytics, Dublin, Ireland*

## Abstract

Intensive grassland management is impacting Europe's semi-natural grassland habitats. Without accurate data on the extent of intensive practices, conservation efforts to reverse biodiversity loss cannot succeed. This study explores how multispectral and synthetic aperture Radar (SAR) imagery and machine learning (ML) can be used to classify management intensity in Ireland. Preliminary results using three land-use classes had overall accuracy between 85 and 91%. Class labels were derived from Eurostat LUCAS survey photographs taken in 2018. Using ML, paddocks within the improved class were identified with ~86% accuracy. Work continues on expanding the model to a regional scale and different levels of intensity. The project also explores how subjectivity in class labelling can be reduced using Deep Learning. The study demonstrates the potential of in-situ photography for validating habitats and land use studies with clear implication for future CAP monitoring.

**Keywords:** management intensity, biodiversity, Sentinel, LUCAS, artificial learning

## Introduction

The expansion of intensive management practices and abandonment of marginal land are critical factors in the continuing decline of Europe's species-rich, semi-natural grassland habitats (Plantureux *et al*., 2005). Ireland has the greatest proportion of grassland cover in the EU. While many Irish farms have high nature value, agricultural intensification and specialization threaten remaining semi-natural habitats (Ó hUallacháin *et al*., 2016). The extent and quality of habitats is poorly understood as there is a lack of farm-scale baseline data that could support biodiversity conservation efforts. Earth observation (EO) satellite data can simplify the task of habitat mapping; however, the disparity between habitat scale and observation scale has hampered habitat mapping in the past. The increasing availability of medium to high resolution EO imagery, coupled with continuing developments in artificial learning, are providing new opportunities for mapping grassland habitats and management (Bekkema and Eleveld, 2018). The objective of this study was to assess the capability of multi-sensor, multi-temporal EO imagery for mapping grassland management intensity as a proxy for grassland habitats. The project also examines whether labelling of land use class can be made less subjective by using Deep Learning algorithms.

## Materials and methods

Land use intensity was characterized for 856 locations using photographic records from the Eurostat 2018 Land Use and Coverage Area frame Survey (LUCAS). LUCAS is a triennial survey that collects harmonized and comparable statistics on land use/ land cover (LULC) and environmental parameters at pre-selected locations across the EU. Initially 3 class labels ("Improved", "Semi-improved" and "Unimproved") were assigned to LUCAS images following project-specific LULC description keys. These locations were intersected with boundary polygons from national vector mapping (OSI PRIME2), with these *a priori* objects subsequently used for object-based image analysis (OBIA) of ESA Sentinel-1 (S1) and Sentinel-2 (S2) imagery. All available images between Jan. 2017 and Dec. 2019 were used (see Figure 1). Satellite imagery were downloaded from the CNES PEPS data repository. S1 SAR interferometric wide-swath images were pre-processed using SNAP software (v.8.0) (orbit correction, edge noise removal, backscatter calibration ($\sigma^0$), Range-Doppler terrain correction) into 3-channel composite images (VH, VV and VH.VV). Using R Statistical Software, individual scenes were aggregated into a 52-image mean time-series corresponding to weeks of the year. Grey-level co-occurrence (GLCM) images (mean, variance, homogeneity, dissimilarity and entropy) were also created

for VV and VH bands (at 5x5, 9x9 kernels). Downloaded S2 images were corrected to Bottom of Atmosphere reflectance using Sen2Cor (v.2.8) and cloud/ shadow masked using MAJA (v.3.2). These were aggregated into a 12-image time-series corresponding to calendar months. Spectral indices (enhanced vegetation index (EVI), normalised difference vegetation index (NDVI), normalised difference water index (NDWI) and normalised difference red edge vegetation index (NDREVI)) were derived. GLCM images were created the S2 Band 8 near-infrared. Descriptive statistics (mean and standard deviation) were calculated for each variable/object. For ML, these data were split (70:30) into training/validation datasets within R using random sampling without replacement. The selected algorithms were random forest (RF) and extreme gradient boost (XGB) algorithms based on 5-fold cross validation. Fine-tuning of hyperparameters was executed using the grid search functionality within "caret". Separate models were tested using S1 only, S2 only and a combination of the two. Dimensionality was reduced using principal components analysis (PCA), as well as targeted variable selection based on the XGB variable importance function. ML was also used to detect paddocks within the "Improved" class. Labels for the binary classification were based on visual inspection of LUCAS photos. RF, XGB, support vector machine (SVM), k-means nearest neighbour (KNN) and neural network (avNNet) algorithms were tested. For all models, thematic accuracy was assessed using the confusion matrix function in "caret" which produces a cross-tabulation of observed and predicted classes (error matrix) with associated accuracy metrics. Overall accuracy (OA) is reported hereafter.


Figure 1. S2 data extracted to a polygon object at a LUCAS point (▲). Inset: Ground level photograph showing extensive management (inset © Eurostat).

## Results and discussion

The management intensity map at 3 classes had 85-91% OA. The best performing model was the XGB algorithm using selected variables (0.911; 95% CI [0.870, 0.943]). However, all models performed well with only 5% difference in error between best and worst models (Table 1).

Table 1. Overall accuracy for management intensity classification (3 classes).

| | S1 | S2 | S1+S2 | PCA | Selected variables |
|---|---|---|---|---|---|
| RF | 0.867 | 0.886 | 0.896 | 0.856 | 0.904 |
| XGB | 0.882 | 0.886 | 0.886 | 0.851 | **0.911** |

Z-tests indicated these differences in OA were not statistically significant ($Z=1.06$; $p \geq 0.144$). Dimensionality reduced dataset using PCA had the highest error but reducing the dataset through variable importance improved accuracy and reduced processing time. The most important overall variables were multispectral data with March VI and texture dominating the top 10 important variables. Spectral indices had greatest influence on classifying the "Semi-improved" class. Dissimilarity and variance were important texture metrics. For SAR, VH.VV was more important than VH or VV individually. Optical and SAR texture metrics were equally important for distinguishing the "Unimproved"

class. ML also showed promise for identifying paddocks within larger fields (Table 2), with 86% OA achieved using SVM and RF on the full dataset.

Table 2. Overall accuracy for paddock detection.

| | SVM | RF | XGB | KNN | avNNet |
|---|---|---|---|---|---|
| Paddock detection | **0.855** | **0.855** | 0.836 | 0.709 | 0.618 |

The spatial variation captured in the texture metrics were important in detecting paddocks using this approach. Research continues on expanding the number of classes and validating the results. The project also attempts to reduce subjectivity in manually labelling data by developing a deep learning model using semi-supervised training methods to automatically classify ground level photographs to distinct management classes. Research is underway to utilize a small number of manually labelled photographs to train a convolutional neural network (CNN) that can scale up classification of ground level photographs with high accuracy.

## Conclusions

This study distinguished three classes of grassland management intensity using a multi-sensor object based approach (OA 85-91%). Additionally, paddocks within larger objects were identified with 86% accuracy. This study demonstrates the potential of combining ground level photography with multi-sensor EO imagery for training and validating management and habitat maps with clear implications for supporting and validating claims under future CAP monitoring requirements.

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# Theme 3. Management and decision support

# The role of remote sensing in practical grassland farming

Green S.[1], O'Hara R.[1,2] and Zimmermann J.[1]

*[1]Dept. Agribusiness and Spatial Analysis, REDP, Teagasc, Ashtown Research Centre, Dublin, Ireland; [2]SFI VistaMilk Research Centre, Moorepark, Cork, Ireland*

## Abstract

The provision of Earth Observation (EO) technology-driven services to grassland farmers has lagged behind those provided to arable farmers. Precision Agriculture (PA) in grassland animal systems has largely focused on Precision Livestock farming (PLF) with the application of technology to grass management limited to improved record keeping and automated planning. New data in the form of European Space Agency Copernicus satellites has stimulated the market for using EO data in grassland management, and stimulated research into the monitoring of grassland types, habitats, and use. This short review looks at currently available grassland commercial PA services that utilize EO data. It explores the range of services on offer and discusses the reception and potential in the grassland management business.

**Keywords**: precision agriculture, digital agriculture, decision support, earth observation

## Introduction

The potential of digital agriculture and Earth Observation (EO) to support the grass-based agricultural sector is widely recognized (Hennessy *et al.,* 2020). The remote sensing community has in the past largely viewed 'grasslands' as a target in the environmental domain, looking at issues around exploitation and classification. However, in the last decade research into the use of remote sensing for understanding grassland dynamics as an agricultural target has grown (Ali *et al.,* 2016). As the research focus has shifted, commercial services exploiting this shift have emerged.

Precision Agriculture (PA) for pastoral systems has focused commercially on the animal, exploiting the space sector through application of location services (Banhazi *et al*., 2012) but a renewed focus on technology for grass management has excited interest in the use of EO on grassland farms. The sector has begun to grow but it is currently nowhere near to the level of the arable and horticulture sectors. In a critical review of PA, Lowenberg-DeBoer and Erickson (2019) note the literature on PA adoption in animal systems is so sparse that they chose to limit their study to arable farming.

Here we present a review of commercial, EO-driven services currently available for use on grassland farms. We identify the type of service offered, focusing only on those services that exploit EO data in some way. Most of the services discovered (between 2/12/2020 and 31/1/2021) focus on cropland but they are included here if they offer some functionality to the grassland farmer. Those functions were explored in a recent review of published articles on remote sensing of grasslands (Reinermann *et al.*, 2020) and may be broadly broken down into mapping relative biomass from a Normalised Difference Vegetation Index (NDVI); empirical approaches to correlating NDVI with ground estimate of biomass; modelling of vegetation biophysical properties; grazing intensity; mowing frequency; general use intensity and management type. We also include basic paddock mapping functionality and integration with farm management systems. While the study is focused on Europe we have included a number of Australian and New Zealand services as the market there is more mature and some do extend their offering into Europe. It must be emphasized that this list can only be a partial snap-shot of what is a very dynamic market, and the offering of the services listed will change and grow. In this short review we ignore satellite-base services created for the insurance market (Vroege *et al.,* 2019), however, noting that regional data on grass yield could be useful to individual grassland farmers with respect to non-forage feed prices in the event of a general fodder supply issue (O'Donoghue *et al.,* 2016).

## Service demand

A review, as recent as 2018, concluded there was insufficient evidence that the growing array of PA tools for grassland had improved management sufficiently to warrant their adoption (Shalloo *et al*., 2018). However, this is a quickly developing market and one that is continually being evaluated.

The SuperG H2020 project recently completed a study of decision support technology for permanent grassland across Europe (Sagoo *et al*., 2020). It identified 127 different tools, five of which used EO data or technology (two of these are developed specifically for grasslands). The H2020 Fairshare project (www.h2020fairshare.eu) looking at the digitization of advisory tools found 214 tools with 12 exploiting satellite imagery, and most were generic online mapping services such as Google Maps. The SmartAKIS portal (https//smart-akis.com), focuses on digital advisory tools, and has registered 430 digital farming products on the market; of these, 55 are marketed at grassland farmers. Of the total, 209 relate to mapping or geolocation, but only 13 explicitly mention the use of satellite observation data and 18 use drones.

The drivers for grassland farmers to take up this technology have also been explored. Irish farmers were surveyed on attitudes to digital agriculture (Skillnet, 2019). Of the 728 farmers surveyed, 6% of beef, 2% of dairy and 9% of sheep farmers were using satellite imagery in some way, compared with 28% of tillage farmers. Availability of broadband was the main barrier (55%) identified, and when asked what would be the main incentive to adopt digital agriculture, cost reduction was the most frequently cited (59%). A study comparing, through interviews, the attitudes of UK and Irish grassland farmers found Irish farmers see 'low cost expansion through grazing' as the dominant model going forward, whereas UK farmers see optimizing grass production regardless of the system as the likely future scenario (Shortall, 2019). Naturally, these differing concepts of the future will drive the type of PA that is adopted in Ireland and the UK and suggest that a 'one size fits all' model of PA for grassland is not the ideal. There is a market for these services, and whilst small, it is growing.

## Available services

Most of the services listed in Table 1 were originally built for arable farmers, and focus on intra-field biomass variation, yield prediction, pest control, and control of variable rate technologies (VRT) on the farm. While research into VRT application for fertilizer and lime is underway, the adoption of VRT on European grassland farms is low. However, the use of the NDVI for examining biomass variability within and between fields is agnostic of vegetation type and can be used by grassland farmers. A small number of the services listed have created specific models to estimate biomass (kg $ha^{-1}$) or growth rate (kg $ha^{-1}$ $day^{-1}$) of grass from satellite data, and these are of more direct use. These figures can be directly fed into grass/feed wedge calculations for farms. Two of the systems, focused on dairy, exploit proprietary sensors in an Internet of Things (IoT) model to provide highly accurate and local information on weather, soil temperature and other variables. The free service CropSat should be highlighted. It generates NDVI maps for digitized fields from current and archive Sentinel 2 imagery, and it allows farmers to explore the potential of this technology without cost.

Grassland mowing and harvesting cycle detection is in demand from paying authorities, policy makers and agricultural insurers (European Court of Auditors, 2020) but this has little interest to the farmer as a direct product. However, mowing, cutting and grazing detection is potentially important in a fully automated grass management software package.

The types of EO-driven services supplied are divided into the following categories:

- Map – Using EO imagery as background to enable mapping out of fields and paddocks. This can be as generic as MyMap from Google or automatic detection of boundaries and management unit.
- NDVI – Provides field scale time series of NDVI data for monitoring relative performance of grass and crop biomass (but does not predict or model actual biomass)
- Wedge – Automatically generates a grass or feed wedge using EO data (not farm records)
- Biomass – Through empirical or other approaches, estimates biomass (kg $ha^{-1}$) or growth rate (kg $ha^{-1}$ $day^{-1}$) from EO data for grass (not yield maps from machinery)
- IoT – A service that incorporates other in-field connected sensors (such as weather stations) to improve EO derived measures of biomass, so called 'Internet of Things'.

The services listed all provide a wider range of data services than those listed. Here we show only those services that use EO.

## Discussion and conclusion

Services that are focused on crops would seem to be well placed to expand into grassland farming services. However, they have been somewhat outpaced by pasture-focused services which understand the needs of the livestock farmer. Intra-field or paddock variation is, for now, of less interest to the grassland farmer than the relative performance between paddocks, expressed as a grass wedge. A number of the listed services generate a grass wedge. Relative scores of biomass have their place, such as in providing a relative benchmark for farmers who are not record keepers, especially as climate volatility makes recalling what is 'normal' or 'average' difficult (Green *et al.,* 2018), However, data-hungry farmers need actual numbers.

Reliability is very important, and issues as a result of cloud cover have been a major drawback for EO in grassland management. However, there are now three strategies employed for dealing with data loss through cloud issues: (i) modelling plant growth to gap fill cloudy acquisitions; (ii) use commercial high temporal, high resolution systems to acquire daily optical satellite imagery; and (iii) use of radar data that penetrate cloud with Vegetation Optical Depth (VOD), rather than NDVI as a biomass proxy (some crop services model growth stage from radar data).

Most of the providers examined in this review, and others (Jarman and Dimmock, 2018), offer little concrete evidence on the actual benefit in terms of yield increase, or reduced input costs on paddocks, instead emphasizing efficiency for the farmer. Furthermore, most of the services have not been fully tested in the challenging, heterogeneous field and soil landscape of European grassland regions. Most of the services are implemented on apps for mobile and tablet.

The services found have focused on grass observations, hoping to eliminate manual data entry on farm walks to record paddock covers. However, there are important elements of grassland management and grazing that do not yet appear to be addressed as potential services, such as soil trafficabilty for animals, total harvest yield for silage/hay, and grassland weed detection and control, among others in the research literature.

There is, as yet, no full service grassland management app that uses satellite data to *automatically* record biomass, growth rate and harvest yield as well as grazing, cutting, slurry spreading events (important as part of nutrient management plan on the farm), and ultimately delivering a weekly report to the farmer of such activities (these reports may play a role in future CAP monitoring and remote cross compliance checks) with a forecast of grass growth for the week ahead. These are all possible, at the moment, and in part are reflected, *in toto*, in the list of services in Table 1.

Table 1. List of identified online digital agriculture services applicable to grassland (FOCUS – (P)asture, (C)rop)

| Name | Service | FOCUS | Notes |
|---|---|---|---|
| Akkerweb | Map, NDVI | P/C | Integrates with VRT and other technologies and with a manual grass measurements recording system (Grip op Gras) |
| FarmSat Geosys | Map, NDVI | C | Management optimization tool |
| Field-Boundary | Map | C | Automatic field boundary mapping form imagery |
| Kore | Map, NDVI | C | Platform to integrate various data sources to provide decision support |
| Pasture.io | Map, NDVI, Biomass, Wedge | P | High resolution high frequency optical mapping.<br>Grass wedge needs reliable data input from farmer.<br>NZ but offers service in EU |
| LIC SPACE | Map, NDVI, Biomass, Wedge | P | Optical gap fills using predicted pasture growth |
| Pasture From Space | NDVI | P | Focus on Range Management |
| Cloud Free Biomass – Vandersat/basf | Map, NDVI | C | Gives daily relative biomass maps using VOD as a proxy for biomass (as NDVI is a proxy for biomass in optical systems |

Table 1. List of identified online digital agriculture services applicable to grassland (FOCUS – (P)asture, (C)rop) – *continued*

| Name | Service | FOCUS | Notes |
|---|---|---|---|
| Anuland-Fieldsense | Biomass, Map, IoT, DSS | P | Primarily uses proprietary sensors on farm to produce outputs - uses EO as background |
| MiSat | Map, NDVI | C/P | Links to variable rate control systems |
| FarmMote | Map, NDVI, Wedge, IoT | P | Augments EO with in-field sensors it calls 'motes' |
| Fieldmargin | Map, NDVI, Wedge | C/P | |
| EDENPA | NDVI, Map, Biomass | P | Australia |
| Cibolabs | NDVI, Biomass, Map | P | Australia |
| CropSAT | NDVI | C/P | This free service maps intrafield biomass variation using Sentinel 2 data. |
| Datafarming | NDVI, Map | C | Australia |
| Contour from Rhiza | Map, NDVI | C | Optical and SAR<br>Primarily a full service digital farming service for crops and soil. Is working toward grassland |
| Climate FieldView | NDVI, Map | C | Provides yield maps for crops but not grassland-integrated into VRT and other PA tech for cropland |
| Cropio | NDVI, Map | C | US farmland management service- focused on crops |
| Agrisat/ | NDVI, Map | C | Uses the open research platform SpiderWebGIS as do many water/catchment projects |
| PastureMap | Map | P | Sensor/farmer input focussed but uses EO as background image. Focused on rangelands in US |
| Deep Planet | | C | DeepPlanet is focused on yield modelling for crops and soil management but has a service in development called Grass signal (c.f. their soil signal product) providing estimates in kg/ha of grassland biomass |

This short review of EO services for pasture shows an emerging technology but a fragmented, fractious market (start-ups that quickly collapse, and services going through multiple owners). A recent theoretical study (Rutuu *et al.,* 2017) has shown the development of digital platforms thrive when there is a high degree of openness between platforms. Providing a set of interoperable services and platforms could therefore be the key to ongoing growth (Bahlo *et al*., 2019).

Web addresses of services listed in Table 1:

| | |
|---|---|
| CropSat | https://cropsat.com/ |
| Akkerweb | https://akkerweb.eu/nl-nl/ |
| FarmSat Geosys | https://www.urthecast.com/geosys/farmsat/ |
| Field-Boundary | https://Field-boundary.com |
| Kore | https://www.soilessentials.com/product/kore/ |
| Pasture.io | https://Pasture.io |
| LIC SPACE | https://www.lic.co.nz/products-and-services/space/ |
| Pasture From Space | http://www.pasturesfromspace.csiro.au/ |
| Cloud Free Biomass | https://vandersat.com/data/cloud-free-biomass/ |
| Anuland- Fieldsense | https://Annuland.ie |
| MiSat | http://www.precisiondecisions.co.uk/agriculture/misat |
| FarmMote | https://farmote.com/ |
| Fieldmargin | https://fieldmargin.com/ |
| EDENPA | https://edenpa.com.au/ |
| Cibolabs | https://www.cibolabs.com.au/ |
| Datafarming | https://www.datafarming.com.au/ |

| | |
|---|---|
| Contour from Rhiza | https://www.rhizadigital.co.uk/contour/ |
| Climate FieldView | https://climate.com/ |
| Cropio | https://cropio.com/ |
| Agrisat | https://agrisat.es/ |
| PastureMap | https://pasturemap.com/ |
| Deep Planet | https://www.deepplanet.ai/ |

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# A novel dynamic model for estimating standing biomass and nitrogen content in grass crops harvested for silage production

Hjelkrem A. G. R., Geipel J., Bakken A. K. and Korsaeth A.

*Division of Food Production and Society, Norwegian Institute of Bioeconomy Research (NIBIO), P.O. box 115, 1431 Ås, Norway*

## Abstract

This paper describes a tool that enables farmers to time harvests and target nitrogen (N) inputs in their forage production, according to the prevailing yield potential. Based on an existing grass growth model for forage yield estimation, a more detailed process-based model was developed, including a new nitrogen module. The model was tested using data from an experiment conducted in a grassland-rich region in central Norway and showed promising accuracy with estimated root mean square error (RMSE) of 50 and 130 g $m^{-2}$ for dry matter yield in the trial. Three parameters were detected as highly sensitive to model output: initial value of organic N in the soil, fraction of humus in the initial organic N in the soil, and fraction of decomposed N mineralized. By varying these parameters within a range from 0.5 to 1.5 of their respective initial value, most of the within-field variation was captured. In a future step, remotely sensed information on model output will be included, and in-season model correction will be performed through re-calibration of the highly sensitive parameters.

**Keywords:** grass growth model, nitrogen availability, sensitivity analysis

## Introduction

Nitrogen is essential for grass growth. While N deficit inhibits growth, surplus N harms the environment through leaching and increased gaseous emissions. Optimized N application is therefore desired, but is difficult to implement due to system complexity. The aim of this study was to develop a new dynamic model with a soil N module, to serve as a tool that enables farmers to time harvests and target N inputs in forage production.

In this study, the design and test of the core model was addressed. A sensitivity analysis was performed on a selection of model parameters to detect the parameters which affect the yield prediction most. Further, the predictive uncertainty in model output induced by these highly sensitive parameters was explored. In the next step, the model will be expanded to enable in-season corrections of selected sensitive model parameters, based on remotely sensed information on above ground standing biomass and proportions of clover.

## Materials and methods

A new process-based grass growth model was developed based on *Grovfôrmodellen* (Bakken, 2016). The model applies to growth of grass swards in perennial leys and estimates dry matter yields (g $m^{-2}$) on a daily basis. The model requires diurnal input of weather data (air temperature, soil temperature, precipitation, global radiation, wind speed and relative humidity), some soil properties (field capacity and plant available water capacity, which may be estimated from texture data), the clover proportion in the swards and some management data (timing and amount of N fertilization and timing of harvests). The overall concept of the model is given in Equation 1, describing the calculation of daily growth of harvestable aboveground dry matter ($\Delta DM_{yield}$):

$$\Delta DM_{yield}(d) = \Delta DM_{pot}(d) \cdot min\big(TI(d), SI(d), WI(d)\big) \cdot NI(d) \cdot AI(d) \quad (1)$$

The potential daily growth of dry matter yield ($\Delta DM_{pot}$) was calculated in line with *Grovfôrmodellen*. Factors known to retard growth were accounted for by indices. Indices of temperature (*TI*), solar radiation (*SI*) and age/ phenological stage of plant development (*AI*) were given as simple equations (Angus *et al*., 1980), while indices of water availability (*WI*) and N (*NI*) were calculated in separate modules. While *WI* was given as the ratio of actual to potential evapotranspiration, *NI* was estimated as the ratio of actual N in the plant to the critical N (Greenwood *et al*., 1990). Plant N uptake was given as

the inorganic plant available N in soil, set according to a maximum uptake, whereas daily soil N content of organic and mineral form was estimated from the processes of N fertilization, clover fixation, nitrification, denitrification, percolation, leaching, mineralization, humification and root death.

To determine the parameters that are the key drivers of the model, a sensitivity analysis (Morris, 1990) was performed to calculate μ* (representing the overall influence of the parameters on model output) and σ (representing interactions with other parameters or nonlinear effects). Further, predictive uncertainty in model output induced by parameter uncertainty was explored by running the model 100 000 times, while allowing the highly sensitive parameters to vary within a range from 0.5 to 1.5 of their respective initial value.

The model was implemented in Matlab (R2019a). It was tested using two datasets with field observations of dry matter yield at Kvithamar in central Norway in 2016, including data from plots with either high or medium levels of N fertilization (Geipel *et al*., 2021). Weather data were obtained from a weather station at the site (daily temporal resolution), soil data were based on soil analyses performed in earlier projects and pedotransfer functions (Riley, 1996), clover proportion at cutting time was given through NIRS analysis (Fystro & Lunnan, 2006) and timing and amount of N fertilization and timing of harvests was recorded.

## Results and discussion

Observed dry matter yield showed high within-field variation, regardless of N level and cutting time (Figure 1). For the treatment with a high N fertilization level (Figure 1a), the model predicted dry matter yield within the centre of the observations for the first cut, while an underestimation with fit within the lower range of observations was found for the second cut. The RMSE between the model output and the mean observed yield was 50 g $m^{-2}$. For the medium dose of N applied (Figure 1b), yield at the first cut was underestimated with fit within the lower range of observations, while yield at the second cut fitted well within the centre of the observations (RMSE of 130 g $m^{-2}$).

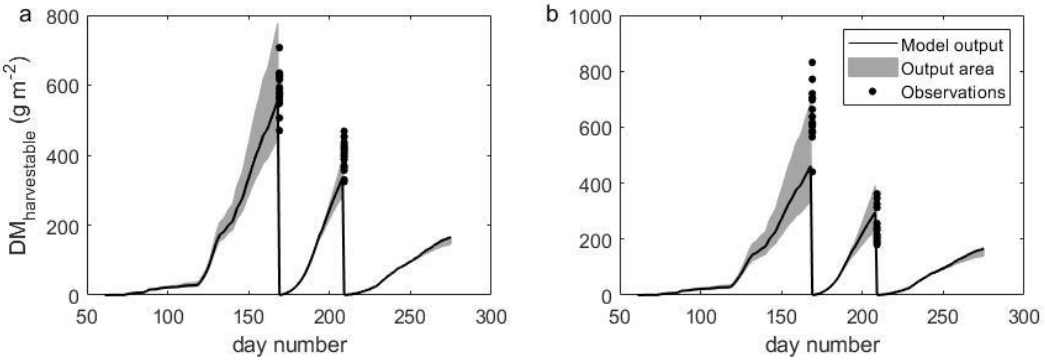


Figure 1. Model output from the grass growth model and observed values from Kvithamar (2016) of harvestable dry matter yield, with high (a) and medium (b) level of N fertilization. The grey area represents variation in model output induced by varying three most sensitive parameters within a range from 0.5 to 1.5 of their respective initial values (see Figure 2).

The N index had an effective and necessary limiting effect on simulated plant growth. Without including the N module, the model generally overestimated grass growth with RMSEs of 330 and 350 g $m^{-2}$, respectively.

Ten parameters of the N module were selected for a sensitivity analysis and the model output appeared to be highly sensitive to changes in three parameters (Figure 2). These parameters were the initial value of organic N in the soil (Figure 2), the fraction of humus in the initial organic N in the soil, and the fraction of decomposed N mineralized.

The predictive uncertainty area in model outputs induced by parameter uncertainty from the three most sensitive parameters was explored and covered most of the within field variation (Figure 1a and b).

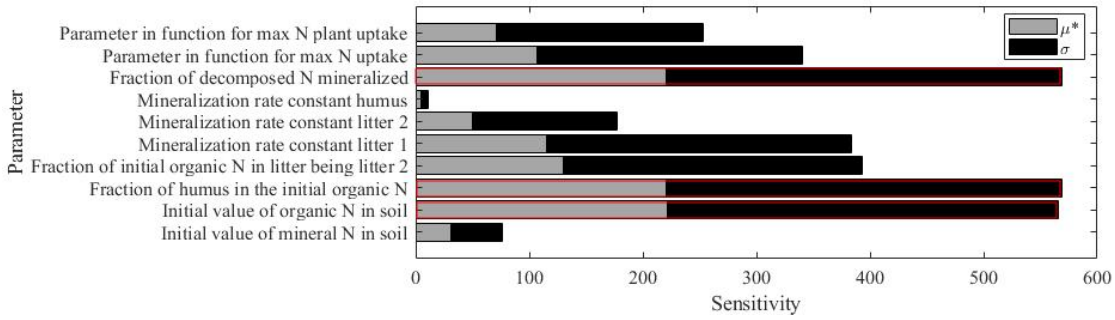


Figure 2. Results from sensitivity analysis of the grass growth model, using the Morris method, given as the overall influence (μ*) and the interaction with other parameters (σ) for ten selected parameters.

In the next model revision, UAV-borne sensing inputs of crop biomass and clover portions will be provided periodically during the run time. When the error term between model output and sensed biomass is not within an acceptable range, the sensitive parameters will be re-calibrated to achieve an improved fit and, subsequently, more robust estimates of site-specific N demand.

## Conclusions and outlook

The newly developed model estimated yield reasonably well. Three parameters within the N module were detected, to which the model outcome was particularly sensitive. The output area spanned by these parameters was calculated, showing a great potential to increase accuracy by using site-specific values for these parameters.

In a next implementation step, routines will be included to enable the model to provide predictions of N demand, needed to reach the full yield potential. Moreover, the model will be able to handle yield and estimates of clover proportion from UAV-borne sensing as additional inputs to re-calibrate the model within the season to further increase its prediction accuracy.

## Acknowledgements

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# Movement behaviour of cattle analysed with GPS data as affected by three different grazing intensities

Hamidi D.[1], Komainda M.[1], Tonn B.[1,2], Harbers J.[1], Grinnell N. A.[1] and Isselstein J.[1]

*[1]University of Göttingen, Department of Crop Sciences, Grassland Science,Von-Siebold-Str. 8, D-37075 Göttingen; [2]University of Göttingen, Center of Biodiversity and Sustainable Land Use, Büsgenweg 1, D-37077*

## Abstract

In order to achieve a sustainable improvement in livestock grazing systems with their long European tradition, there is a need to improve understanding of behaviour of cattle on pasture. Maintaining the botanical and structural balance of heterogeneous pastures is becoming significant especially in the context of climate change. In this study, the long-term cattle grazing experiment 'FORBIOBEN' with its three paddock-scale grazing intensities (GI) [moderate (M), lenient (L), very lenient (VL)] each replicated thrice, is used to investigate movement and diurnal patterns of cattle behaviour in relation to the grazing intensity and season. The study took place in the spring and autumn grazing events during four periods between May 2017 and July 2020. Nine pregnant suckler cows were equipped with GPS collars, which record both position and activity of the animals at minute intervals. A strong diurnal pattern became evident with a shift in the activity peaks during the autumn period. The highest effort in walking was found in M compared to L and VL for three grazing periods. We discuss these results against the background of the suitability of cattle tracking for pasture management and vegetation parameters (herbage on offer, herbage allowance, variability of herbage on offer).

**Keywords:** GPS tracking, walking distances, precision livestock farming, diurnal patterns

## Introduction

The behaviour of cattle on pasture is linked more or less to their locomotion, as large parts of their daily activity refers to grazing which is usually conducted while walking. Therefore, consideration of walking seems to play a key role in an attempt of behavioural understanding.

In a study by Homburger *et al.* (2014), only 6.7 % of movement was accounted for by walking without grazing. In a study by Baudracco *et al.* (2013) cows on a pasture with lower herbage allowance spent more time walking. Foraging resources are the most obvious drivers of grazer distribution at pasture (Adler *et al.,* 2001). The present study, therefore, compares three different GIs concerning the daily and hourly walking distances per cow. The question was to assess to what extent the grazing intensity and, hence, the availability or distribution of herbage, controls the activity of grazing cattle on semi-natural grassland ecosystems. Such information is needed if any decision-support tools in future smart farming systems will be based on the spatial animal movement and its prediction.

## Materials and methods

The investigation was embedded in the long-term cattle grazing experiment 'FORBIOBEN' (located in Relliehausen, Solling Uplands, Lower Saxony, Germany, which was established in 2002 (Isselstein *et al.,* 2007) and has been maintained in its current state since 2005. Since then, it compares three intensities of cattle grazing described by different target vegetation heights based on compressed sward height measurements, hereafter M: moderate grazing (6 cm), L: lenient grazing (12 cm) and VL: very lenient grazing (18 cm target vegetation height), replicated in a randomized block design of three paddocks (1 ha each) per grazing intensity. The management refers to a continuous grazing system in a put and take approach. During each stocking season (Apr/May- Sep/Oct), 27 pregnant, non-lactating Fleckvieh suckler cows grazed in all three grazing intensities, randomly assigned in groups and distributed among the paddocks. The three most important grasses in the grazing trial in 2017 were *Festuca rubra*, *Lolium perenne* and *Cynosurus cristatus* and for the *dicot* species: *Taraxacum officinale*, *Trifolium pratense* and *Galium mollugo.*

Table 1. Herbage on offer (HO), per grazing intensity in g DM m$^{-2}$ ± sd

| | **2017 (18 May – 14 Jun)** | **2019 spring (24 May – 27 Jun)** | **2019 autumn (6 Sep – 22 Sep)** | **2020 (11 Jun – 12 Jul)** |
|---|---|---|---|---|
| HO in **M** | 235.1 ± 97.5 | 108.9 ± 70.6 | 81.5 ± 100.3 | 80.9 ± 54.2 |
| HO in **L** | 318.7 ± 120.4 | 209.7 ± 100.6 | 166.5 ± 108.8 | 156.1 ± 69.2 |
| HO in **VL** | 354.5 ± 123.8 | 222.0 ± 105.6 | 194.2 ± 119.9 | 172.2 ± 77.4 |

At the beginning of each period, one cow per GI and replicate (randomly chosen) was equipped with a Vectronics GPS Plus (VECTRONIC Aerospace GmbH, Berlin) collar (weight: 1.36 kg). The GPS sensors in the collar recorded a signal about the location of the animal within the pasture. The activity sensor recorded data on the animal's activities. The main target variable with two temporal scales in the present study was the distance (m) per animal per day and also per hour within day. Geographic coordinates in Universal Transverse Mercator coordinate system (UTM) format were used to calculate the distance between two sequential positions with the Pythagorean theorem. The results were summed for hourly and daily (24-h) periods. The herbage on offer (Table 1) and its spatial variability in terms of the standard deviation (SD herbage) were derived from regular compressed sward height measurements and calibration cuts. Statistical analyses per period were carried out with R, with linear mixed effects models using the package 'nlme'. The daily distance was regressed on the fixed effects of grazing intensity and date as well as their interaction. The cow nested in block was modelled random. Then a model reduction was performed from the global model using the MuMIn package. The model with the lowest AICc (Akaike Information Criterion for small sample sizes) was chosen as the final model. The hourly distance was log-transformed before analysis in order to improve normality of residuals. The period-wise average herbage on offer (HO) and the spatial heterogeneity of HO (SD herbage) were evaluated with the grazing intensity as fixed and block as random effect.

## Results and discussion

The interaction between hour per day and the grazing intensity affected the hourly walked distance in all periods $P < 0.001$. Walked distances in grazing intensity M were largest for most periods (but not in 2020), while L was lowest for most periods (not in 2017) and VL tended to range between them. Cattle usually take several steps between bites, which means that the activity of grazing is associated with walking. Difficulties in herbage intake arise when the vegetation is very short, sparse, or long and old, all of which will cause a larger requirement for grazing time and, hence, walking. In this respect, the pasture sward properties have a large effect on the daily grazing time, since cattle prefer leafy and digestible herbage (Cuchillo Hilario *et al.,* 2017) and will seek this actively. With respect to the shorter vegetation and the lower amount of herbage on offer, the cows grazing in treatment M probably needed to enlarge their daily grazing area and, hence, their effort for walking. In extensively grazed grassland, the vegetation resembles a mosaic of foraging sites besides avoided ones, which indicates a higher heterogeneity (Tonn *et al.,* 2018). With regard to the walking distance, it can be assumed that the pasture (heterogeneity) responds to animal movement as well as vice versa. Cattle return to known spots, as long as these spots are productive; therefore forage search is predictable (Fehmi *et al.,* 2002). It is widely accepted that cattle activity shows diurnal patterns especially for the activity of grazing which is mainly correlated with the duration of daylight (Figure 1).

## Conclusions

When evaluating efforts of cattle movement, the GI is probably no reliable indicator. In our study, cows increased their efforts under both the most intensive and also the least intensive grazing treatment. Thus, the herbage availability in terms of herbage allowance and also the spatial distribution and the heterogeneity of the sward have to be taken into account when aiming to design decision support tools in future precision livestock farming technologies.

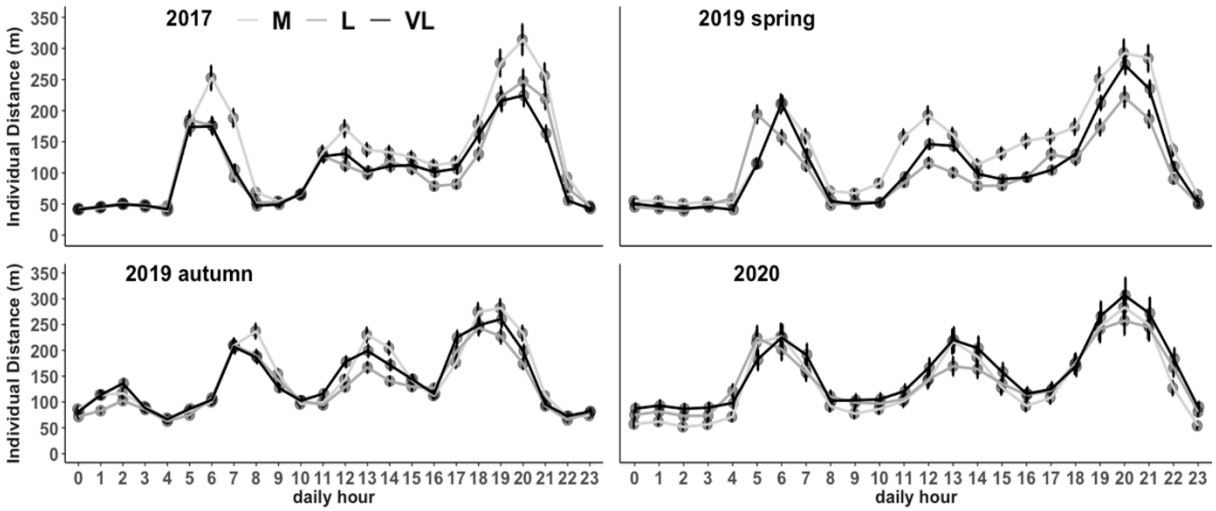


Figure 1. Estimated means (±SE) of the average hourly distance (m) as influenced by the grazing period, grazing intensity and hour per day. M: moderate, L: lenient, VL: very lenient

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# Detection of *Senecio jacobaea* in drone images, using a machine-learning approach

Petrich L.[1,2], Stoll A.[2] and Schmidt V.[1]

*[1]Institute of Stochastics, Ulm University, Germany; [2]Hochschule für Wirtschaft und Umwelt Nürtingen-Geislingen, Germany*

## Abstract

*Senecio jacobaea* (S.j.) often grows in extensive grassland and poses a threat to farm animals due to toxic substances. Effective weed control requires site-specific counter measures targeting the toxic plants. This requires precise knowledge of the locations of the S.j. Here we present an approach adapted from success with *Colchicum autumnale*. When the flowers were blooming, the fields were mapped using a consumer-grade camera mounted on a drone. The resulting images can then be stitched together to obtain an orthomosaic of the whole field. The S.j. flowers were located in the images using a convolutional neural network with a U-Net architecture. The relatively low number of labelled ground truth images was compensated by applying image augmentation techniques during the training of the neural network. On the test dataset, 95% of the predicted S.j. flower locations were correct (precision), and 70% of the true locations were found by the detector (recall).

**Keywords:** *Senecio jacobaea*, convolutional neural network, drone image, object detection

## Introduction

*Senecio jacobaea* (S.j., also known as *Jacobaea vulgaris*, or ragwort) is a flowering plant with very distinctive 15-20 mm yellow flowers clustered in inflorescences of about 20-60 flowers (Söchting, 2010). Because of its toxicity, it poses a threat to grazing animals. On pastures, animals usually avoid the plant. However, the poisonous substance is conserved in hay and silage where the animals are unable to detect and avoid it. S.j. can be found on pastures or extensive grassland sites and is often dispersed from fallow land to agricultural land. Grassland with a high density of S.j. must be ploughed and resown with new grass. If only a few plants occur, they must removed manually. Both measures are unsatisfactory, as they require additional costs for machines and labour. Therefore, an automated and selective weed control system is required. For this, it is necessary to have precise information about the locations of the S.j. plants. For this reason, the aim of the research reported here is to investigate a method that locates S.j. flowers in images taken by a drone flying over the grassland site. An automated treatment tool could then be developed, which is able to control the weed efficiently based on the predicted S.j. locations. In Petrich *et al.* (2020) the considered detector (which we call flower detector in the following) is presented for locating *Colchicum autumnale* (C.a.) flowers in drone images. The approach is based on a convolutional neural network and was originally applied to S.j. in Forster (2020), on which the present paper is based. In contrast to other attempts in the literature (Zacharias, 2017), the flower detector does not rely on manual feature engineering, but rather learns the features of the flowers through the training. This makes it applicable to different kinds of plants (given suitable training data).

## Materials and methods

The necessary image data were obtained on two grassland sites near Bad Überkingen/Burren and Konstanz, Baden-Württemberg, Germany. During the acquisition time between 22 July and 21 August 2019, the S.j. were approximately 50-60 cm in height. On the site near Burren, the surrounding vegetation was about 25-30 cm tall and almost the same height as the S.j. on the site near Konstanz. The camera (Sony alpha 7 RII with a Sony lens FE 12-24 mm 4G and a resolution of 7952x5304 pixels) was mounted on a drone (Octocopter MK ARF Okto XL 4S12) flying roughly 10 m above ground.

In order to keep the workload feasible, 13 disjoint drone images were chosen for manual labelling. For this, each inflorescence (or separate flower) was circumscribed by a polygon (instead of a coarser bounding box as in Petrich *et al.* (2020)), and all polygons belonging to the same drone image were drawn to a binary image ('ground truth segmentation maps') of the same size as the drone image. The result was a dataset of 13 colour drone images and corresponding ground truth segmentation maps, the

latter of which described the locations and rough shapes of the S.j. flowers and were thus the desired outputs of the trained detector.

This ground truth dataset was split into a training dataset (comprised of 7 drone images and segmentation maps), a validation dataset (3 images), and a test dataset (3 images) at random. For details regarding the flower detector and its calibration to data, we refer to Petrich *et al.* (2020) and concentrate only on the differences in the following. The segmentation maps of the training dataset were further refined by removing all non-green pixels from the labelled polygons and were used to train different models of the flower detector (each having different hyperparameters) under the application of image augmentation. For the post-processing parameters, bounding boxes of the S.j. flowers were required, which were obtained by computing the bounding boxes of each connected component of the refined segmentation maps. Based on the validation dataset, the best model of the flower detector was selected. In total 48 models were evaluated corresponding to all combinations of the considered hyperparameters (four values for the base number of convolutional layers, three values for the initial learning rate, whether to use batch normalization, and which loss function to use, see Petrich *et al.* (2020)). The test dataset was used to judge how the (selected) flower detector model performs on previously unseen image data.

## Results and discussion

The best model resulted from the flowing hyperparameters. It employed the (weighted) cross-entropy loss function and batch normalization, had a base number of convolutional filters of 8, and an initial learning rate of 0.00014211.

Table 3. Cluster-based evaluation results for the validation and the test datasets of the best flower detector model

| | Validation | | | | Test | | | |
|---|---|---|---|---|---|---|---|---|
| | Summary | Image 1 | Image 2 | Image 3 | Summary | Image 1 | Image 2 | Image 3 |
| #TP | 298 | 103 | 194 | 1 | 225 | 206 | 13 | 6 |
| #FP | 63 | 25 | 22 | 16 | 11 | 2 | 8 | 1 |
| #FN | 49 | 26 | 21 | 2 | 96 | 96 | 0 | 0 |
| #TN | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Precision | 0.826 | 0.805 | 0.898 | 0.059 | 0.953 | 0.990 | 0.619 | 0.857 |
| Recall | 0.859 | 0.798 | 0.902 | 0.333 | 0.701 | 0.682 | 1.00 | 1.00 |
| F2 score | 0.852 | 0.800 | 0.902 | 0.172 | 0.740 | 0.727 | 0.890 | 0.968 |

Table 1 shows results of the cluster-based evaluation. Each labelled polygon of a drone image was considered and counted as a true positive (TP) if there was a foreground cluster in the predicted output of the (selected) flower detector model that intersected this polygon. If there was no corresponding prediction, it was a false negative (FN). All foreground clusters that did not intersect a polygon were considered false positives (FP). From these values the precision (‘probability that a predicted foreground cluster is actually a S.j. flower’), the recall (‘probability that a S.j. flower was detected’), and the F2 score (an aggregated value of precision and recall with more weight on the latter) were computed (Goodfellow *et al.,* 2017).

Table 1 shows good precision (0.826) and recall (0.859) for the validation dataset. More important are the results for the test dataset, where a very high precision of 0.953 could be achieved and a reasonable recall of 0.701. A more in-depth analysis showed that many of the false positives were yellowish leaves, but there were also cases where it was not clear from the image whether a yellow flower actually should have been labelled as S.j. flower. False negatives, on the other hand, tended to be smaller isolated flowers. The fact that all false negatives in the test dataset and most of the true positives were from a single drone image indicates that the ground truth dataset might have been too small for a definitive judgement on the flower detector's performance to locate S.j., and further interventions are necessary.

Compared to the results presented in Petrich *et al.* (2020), the recall is decreased (0.701 for S.j. vs. 0.986 for C.a.). Even though the yellow flowers of the S.j. might be considered as not as distinct as the purple flowers of the C.a., the number of false positives and therefore the precision is better (0.953 for S.j. vs. 0.571 for C.a.). It is important to note that the ground truth dataset is with 13 drone images compared to 56 drone images (of the same resolution) much smaller in the present paper. Moreover, the interfering objects, which were one of the main sources of misclassification in Petrich *et al.* (2020), did not occur in the S.j. ground truth dataset and the resilience of the model regarding those could thus not be evaluated.

## Conclusions

It was shown that the flower detector originally developed for C.a. in Petrich *et al.* (2020) can be used to locate S.j. in drone images with a recall of 0.70 and a precision of 0.95 on the test dataset. These initial results are very promising, but further research is needed in order to evaluate the detector's performance on larger and more diverse datasets (different site locations, surrounding vegetation, etc.). Another possibility is to train multiple models based on different dataset splits (e.g. using cross-validation) and average their performances. For this, however, it is necessary to cope with the increased computational costs.

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# The effect of virtual fencing technology on grazing behaviour: differences in herbage consumption

Grinnell N. A.[1], Hamidi D.[1], Horn J.[1], Riesch F.[1], Komainda M.[1], Ammer S.[2], Traulsen I.[2] and Isselstein J.[1]

*[1]University of Göttingen, Department of Crop Sciences, Grassland Science, Von-Siebold-Str. 8, D-37075 Göttingen; [2]University of Göttingen, Department of Animal Sciences, Albrecht-Thaer-Weg 3, D-37075 Göttingen*

## Abstract

Virtual fencing (VF) technology applies stimuli to control grazing livestock without physical barriers. VF is a promising innovation in grazing livestock management, as it allows remote monitoring of animal movements and improved pasture utilization. This study aimed to determine whether the application of novel VF technologies in cattle grazing systems affects grazing animal forage intake. For this, 24 heifers (Simmental, age average: 462 days, live weight average: 396 kg) in 6 experimental groups were equipped with NoFence VF collars (® Nofence, AS, Batnfjordsøra Norway). Control groups had only physical fences (PF) and received inactive VF collars. In 3 periods of 12 days, one control and treatment group each were grazed on adjoining paddocks (866.5 ± 32.7m$^2$) for 5h daily. Forage biomass samplings were done on days 1, 8, and 12 of each period in both paddocks. Herbage dry matter accumulation was determined by manual clipping near the soil surface. Data analysis showed that sampling time affected dry matter availability and, thus, herbage intake (HI) ($P<0.001$). However, there was no significant difference in HI between treatments. Therefore, it can be concluded that the VF technology did not affect HI of grazing heifers, even though it was previously unknown.

**Keywords:** smart farming technology, virtual fencing technology, animal welfare, herbage intake, grazing management, sustainable farming practices

## Introduction

Grasslands are an important element in European landscapes (Veen *et al.,* 2009) and large herbivores play a decisive role in preserving this extensive biome. Management practices in pasture-based agricultural production systems greatly influence the extent of greenhouse gas (GHG) emissions, carbon dioxide retention, and the effect on biodiversity. Extensive and moderate grazing with rotational stocking has been shown to positively support these ecosystem services (Zhang *et al*., 2015; Zubieta *et al*., 2021). Furthermore, management strategies with low-intensity and high-frequency grazing can have positive effects on animal performance, as the plant physiological state influences the animal's short-term herbage intake (Marin *et al*., 2017; Savian *et al*., 2021). However, labour requirements are higher in rotational grazing and similar practices compared to continuous grazing systems (Walton *et al.*, 1981).

Virtual fencing (VF) is a promising innovation in grazing livestock management, as it allows remote monitoring of animal movements and could improve pasture utilization while reducing the required labour for fencing and, thus, the economic viability of the production system. As VF is a novel technology, however, its effects on animal behaviour and productivity are largely unknown. Investigating possible effects on animal productivity is essential for establishing the economic benefits of applying the technology compared to established grazing systems. The aim of this study was, therefore, to determine whether the application of novel VF technologies in cattle grazing systems affects animal forage intake.

## Materials and methods

The trial was approved by the animal welfare service of LAVES (Lower Saxony State Office for Consumer Protection and Food Safety - reference number: 33.19-42502-04-20 / 3388) and was conducted in August and September 2020 in the Solling Uplands, Germany, with 24 heifers (Simmental, 462 ± 17.3 days age and 396 ± 32.7 kg live weight average) that were randomly assigned to six treatment groups. The effect of two fencing system treatments, i.e. virtual fence (VF) and a physical fence (PF) control, on forage intake was assessed during three subsequent 12-day grazing periods. Each period, the two groups were grazed five hours daily on adjoining paddocks of 1000 m$^2$ size, so treatment groups refer to a combination of fencing system x period. For training purposes, an exclusion

zone was established within the paddocks with a VF or a PF-line (for details see Hamidi *et al*., 2021; these Proceedings). This exclusion zone was reduced in size after 8 days in each period. Due to the exclusion zone, the total paddock size was reduced to an overall average of 866.5 ± 32.7 $m^2$. The VF groups were equipped with active, the control groups (PF) with inactive NoFence collars (® Nofence, AS, Batnfjordsøra Norway). Sward height measurements, using a rising plate meter (30 cm diameter, 200 g plate weight), and forage biomass sampling were done in both control and VF paddocks at the beginning, the middle, and the end of each 12-day grazing period on days 1, 8 and 12, respectively. For this, the grass sward was clipped near the soil surface on two locations within paddocks using electric shears. Herbage dry matter accumulation was determined after drying the samples at 60°C for 48 h. Using a linear mixed-effects model in R software, the forage availability in dry matter (DM) per $m^2$ was regressed on the fixed effects of fencing system and day of sampling within the period as well as their interaction. The period was used as random factor. Levels of significant influencing factors were compared post hoc using Tukey's HSD test.

## Results and discussion

The fencing system had no significant effect on the forage availability, which was affected only by the sampling date (P<0.001). Forage availability was significantly greater at the beginning of each period than the later samplings (Figure 1). This is to be expected, given that the animals grazed 5 hours per day in the plots. The average forage availability across periods in the VF treatment was 340, 255, and 211 g DM $m^{-2}$ at the start, middle, and end of the period, respectively. In the PF treatment, the corresponding average forage availability was 326, 213, and 160 g DM $m^{-2}$, respectively. The fencing system treatment, thus, did not affect forage intake of the grazing heifers. In the PF treatment, the average forage intake was 3.1 kg DM per animal per day in the first eight days and 2.9 kg DM per animal per day in the last four days, respectively. In the VF treatment, the average forage intakes were 2.3 and 2.4 kg DM per animal per day in the first eight and last four days, respectively.

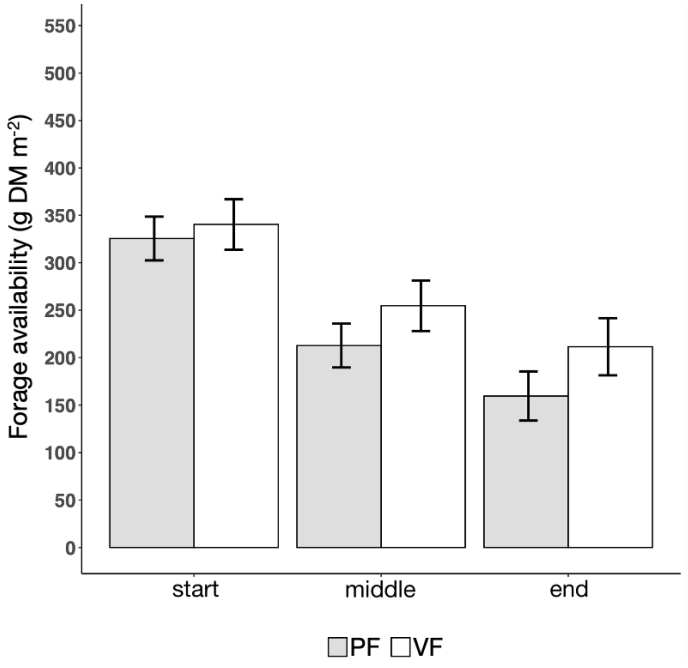


Figure 1. Estimated means of forage availability in g dry matter (DM) $m^{-2}$ (±standard error), on day 1 (start), day 8 (middle), and day 12 (end) of the experiment for cattle groups with physical fence (PF) and virtual fence (VF).

## Conclusions

The absence of significant differences in forage availability between treatments in our preliminary results suggests that the VF technology does not affect herbage intake of growing young grazing cattle. Further investigations of individual live weight gain, forage quality, and forage digestibility along with stress

parameters will enable a holistic evaluation of the VF technology, to assess the efficiency of utilization of pasture herbage and effects on the animal and agronomic outcomes.

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# Monitoring of water content in legume seed production after crop desiccation using multispectral UAV images

Gaier L., Klingler A., Schaumberger A. and Krautzer B.

*Agricultural Research and Education Centre (AREC) Raumberg-Gumpenstein, 8952 Irdning-Donnersbachtal, Austria*

## Abstract

In seed production, a low water content of the crop before the harvest is of great importance. Pre-harvest crop desiccation devitalises the vegetation and consequently lowers the water content of plants to minimize machine load and drying costs. Simple and fast procedures which provide near real-time information about the current crop status are essential for the further success of seed production. The major aims of the study were (i) to determine the effects of three different herbicides used for crop desiccation in the seed production of birdsfoot trefoil (*Lotus corniculatus*) and snow clover (*Trifolium pratense ssp. nivale*). Subsequently we determined (ii) whether remote sensing technologies can be used to display the differences between the treatments. We performed the herbicide applications two (*L. corniculatus*) / three (T. *pratense ssp. nivale*) days before threshing, with a control plot serving as reference in both crops. A multispectral camera, mounted on an unmanned aerial vehicle was used to acquire spectral images from the plots before the herbicide application and before threshing. We harvested green-material and seed samples from all plots and analysed them for residual moisture content. Simple vegetation indices showed very promising results when comparing them with dry matter content of the plant biomass.

**Keywords:** seed production, desiccation, remote sensing, NDVI

## Introduction

Seed production of site-adapted grassland species provides the basis for stable and persistent forage crops, high forage quality and yields. However, due to the often-unfavourable site characteristics and the rapidly changing weather conditions, a successful harvest often proves difficult. Multispectral images from unmanned aerial vehicles (UAV) can provide timely, fast and cost-effective information of the current status of the crop (Wijesingha *et al*., 2020). Vegetation indices, for example the Normalized Difference Vegetation Index (NDVI), derived from these multispectral images can significantly support optimal management decisions in agriculture (Atzberger, 2013).

In small-grain legume seed production, due to rapid seed shedding after seed maturity, the time window for harvesting is very narrow. A low water content of the crop is of great importance to minimize machine load and drying costs. In the case of pre-harvest crop desiccation, the vegetation is devitalised with chemical herbicides to lower the water content of plants allowing an earlier harvest. In legume seed production this practice has been used for more than 60 years (Wiggans *et al*., 1956).

Some of the herbicides used in the past were banned or are in the process of being banned due to adverse effects on the environment or users. Due to the worldwide practice of crop desiccation among many different crops (Moyer *et al*., 1996; He *et al*., 2015), the performance of alternative herbicides also needs to be tested on an ongoing basis.

The major aims of the pilot study were (i) to determine the effects of three different herbicides used for crop desiccation in the seed production of snow clover (*Trifolium pratense ssp. nivale*) and birdsfoot trefoil (*Lotus corniculatus*) and (ii) to determine whether NDVI derived from multispectral images can be used to display the different efficiencies between the herbicides.

## Materials and methods

The trials were carried out in Baumgartenberg (Austria 48°13N, 14°45E; 237 m a.s.l.) in August 2020. We performed the herbicide applications two (birdsfoot trefoil) / three (snow clover) days before threshing, with a control plot serving as a reference in both crops. Herbicide I contains the chemical active ingredient *Diquat* (concentration 200 g $l^{-1}$), the application rate was 1.4 l $ha^{-1}$ dissolved in 300 l of water. This herbicide was in standard use for many years but is no longer approved in the EU (Exemption

permit for legume seed production in 2020 in AT). Herbicide II contains the chemical active ingredient *Carfentrazone-ethyl* (concentration 60 g $l^{-1}$), the application rate was 1 l $ha^{-1}$ dissolved in 300 l of water. Herbicide III contains the chemical active ingredient *acetic acid* (concentration 100 g $l^{-1}$) and we used it with an application rate of 300 l $ha^{-1}$. The plots had dimensions of 750 m² for snow clover and 900 m² for birdsfoot trefoil, except for the control group, which had 180 m².

We used the model MK8-3500 (www.mikrokopter.de) as the UAV platform with a maximum load of 7800 g. We mounted the MAIA S-2 multispectral camera, which is equipped with the identical wavelength intervals as the Sentinel-2 satellite of the European Space Agency (Nocerino *et al*., 2017). We combined the single spectral images to orthomosaics and calculated the NDVI. We conducted the multispectral acquisitions at two different times. We calculated the NDVI for the entire study area from images we took shortly before the herbicide application to record the initial situation (t1). To see if there is a correlation between the different herbicides and the signal of the multispectral image, we calculated the mean NDVI for the individual plots, subtracting a buffer area at the edges and the area of the wheel tracks from images we took shortly before the threshing (t2). To determine the desiccation effect of the herbicides we sampled 1 kg of the threshing residuals (straw = stems and leaves) from the middle strip of the plots in triplicate to compare the moisture content of the different treatments. We dried the samples with a warm air-drying system (50° C) to determine the dry matter content (DM) afterwards using NIRS spectroscopy.

## Results and discussion

The results (Table 1) show a strong negative correlation between NDVI and DM content over both cultures ($R^2$ =0.945). The DM contents for both crops were lowest in the control group. This was in line with expectations, as these plants were apparently greener than in all other groups. The highest DM contents were achieved in each case in the plots treated with herbicide I. In snow clover, the plots treated with herbicide III showed slightly higher DM contents than the plots of herbicide II. In birdsfoot trefoil, the areas treated with Herbicide II showed slightly higher DM contents than the areas treated with Herbicide III. Based on these results, Herbicide I showed the best desiccation effect. Herbicides II and III showed significant effects compared to the control group, but the performance was not as strong as with Herbicide I. The NDVI of the control group decreased slightly in both crops between t1 and t2. The maturation process of the plants can explain this as they were in the seed ripening stage and natural drying occurred between the t1 and t2.

At t2, the control group showed the highest NDVI and the herbicide I treated plots the lowest NDVI for both crops confirming the applicability of this remote sensing technique for water content monitoring in legume seed production.

In both crops, there were no differences in NDVI between herbicide II and herbicide III.

Table 4: Normalized Difference Vegetation Index (NDVI) and DM content before and 3 days after crop desiccation

| | *Lotus corniculatus* | | *Trifolium pratense ssp. nivale* | |
|---|---|---|---|---|
| | NDVI | DM g $kg^{-1}$ | NDVI | DM g $kg^{-1}$ |
| t1 control group | 0.71 | | 0.34 | |
| t2 control group | 0.64 | 152.3 | 0.28 | 333.9 |
| t2 herbicide I | 0.37 | 231.8 | 0.10 | 365.2 |
| t2 herbicide II | 0.50 | 185.5 | 0.13 | 355.9 |
| t2 herbicide III | 0.51 | 167.4 | 0.13 | 359.8 |

## Conclusions

All herbicides were able to enhance crop desiccation and decreased the NDVI of the crops. Herbicide I was most effective in increasing the DM content this could also be shown in the decreasing NDVI. In relation to the control group, the alternative herbicides II and III showed in both crops that they were able to speed up desiccation.

Remote sensing technology may be a suitable tool in the future to show differences in the desiccation of seed productions and supply information to improve management. In order to validate the results found in this pilot study, further research is necessary.

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# Training cattle with virtual fences on permanent pastures

Hamidi D.[1], Grinnell N. A.[1], Horn J.[1], Riesch F.[1], Komainda M.[1], Ammer S.[2], Traulsen I.[2] and Isselstein J.[1]

*[1]University of Göttingen, Department of Crop Sciences, Grassland Science, Von-Siebold-Str. 8, D-37075 Göttingen; [2]University of Göttingen, Department of Animal Sciences, Livestock Systems, Albrecht-Thaer-Weg 3, D-37075 Göttingen*

## Abstract

Grazing animals, especially dairy cattle, have long been a feature in the cultural landscape of Central Europe. Smart farming technologies are one way to improve pasture management. In this study, the virtual-fencing technology (Nofence) was used to manage heifer grazing in an attempt to establish a training protocol. The heifers had not experienced virtual fencing previously. Training took place on small paddocks (1000 $m^2$). Two treatments (four heifers per group) were compared in three repetitions (each of 12 days). One virtual-fence-line, which is set up by GPS coordinates (the collars send acoustic signals followed by an electric impulse as a warning if the animals approach the line), separated the pasture of the virtual-fence-group into accessible or non-accessible areas. The control group had a physical-fence-line. Each repetition followed the next successively on different paddocks with a new group. Training was divided into three sections: visual support of the virtual fence by a physical barrier (first 2 days), only virtual border without visual support, moving the virtual-fence-line (on day 8). Results showed that each heifer was able to learn the virtual fencing cues. The main aspects of cattle behaviour on pasture were not affected by the physical/virtual-fence-line.

**Keywords:** associative learning, smart farming technology, animal welfare, time budgets

## Introduction

Smart farming technologies (especially virtual fencing (vf)) might be the key drivers to reconcile agronomic and ecological interests under the premise of bringing livestock back into the landscape. Vf-boundaries can be shifted whenever it is desired (Campbell *et al.,* 2017) and herbage allowance can easily be changed. This represents an opportunity for improved pasture management, especially for environmentally sensitive areas, where maintenance and implementation of physical fences (pf) are difficult. In the current study, we used vf-collars (Nofence, Norway), which emit acoustic signals as the cattle approach the vf-line. An electrical impulse is administered if the animal continues moving forward. Conditional learning should ensure that the cattle become trained over time to avoid the electrical impulse by reacting to the acoustic signal. Cattle behaviour on pasture should not be affected. In the present experiment, cattle behaviour was studied in the vf-system compared with a common pf-system. As the training of individual cattle is impractical in a commercial setting (Colusso *et al.,* 2020), we used groups of four heifers each to develop a training protocol that would allow safe learning of the vf-technology and could be used in future for more detailed studies on the potential of vf for grassland management.

## Materials and methods

The present experiment, located in Relliehausen, Solling Uplands, Lower Saxony, Germany, investigated the (learning) behaviour of 24 heifers (Fleckvieh, 14-16 months, 320-451 kg initial weight) grazing in two treatments (vf/pf) compared over three periods. They were trained in two paddocks (1000 $m^2$ each) every day between 10 a.m. and 5 p.m. After the daily training, cattle were housed and had access to hay in a stable adjacent to the training site. An exclusion zone within the paddocks was established with a vf/pf-line. Four heifers per group were compared in three successive periods (12 days each) from 17 Aug 2020 to 25 Sept 2020. All heifers wore Nofence collars (® Nofence, AS, Batnfjordsøra Norway), which were inactivated for the pf-groups. Acoustic signals (increasing melody) followed by an electric impulse if the animals continued moving towards the vf-line were emitted by the activated collars of the vf-groups. For the vf-groups, the training periods were divided into different learning sections to adapt the animals to the vf (Figure 1).

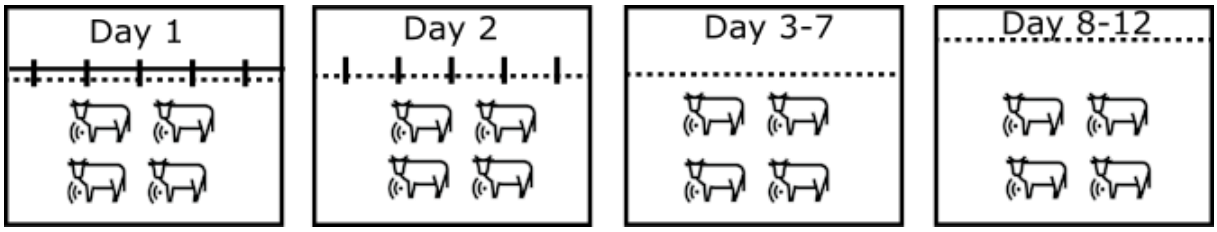


Figure 1. Learning sections of the virtual fencing group: day 1 complete pf + vf-line, day 2 fence posts + vf-line, day 3 to 7 only vf-line, day 8 to 12 shifted vf-line

During the whole experiment, the cattle behaviour was continuously observed (one observer per group continuously recorded the individual behaviour of each of the four animals; 2 h a.m., 2 h p.m.) using the app 'Observasjonslogger' by Morten Sickel. Statistical analyses were carried out with R 4.0.3. Linear mixed effect models were used with the fixed effects: group, observation day, time of day (a.m./p.m.) and the nested random effects: period, group, animal-ID. The trial was approved by the animal welfare service of LAVES (Lower Saxony State Office for Consumer Protection and Food Safety – ref. number: 33.19-42502-04-20 / 3388).

## Results and discussion

No heifer crossed the vf-line during the experiment. Average numbers of acoustic and electric signals per heifer and hour were 2.7 and 0.3, respectively (Figure 2).

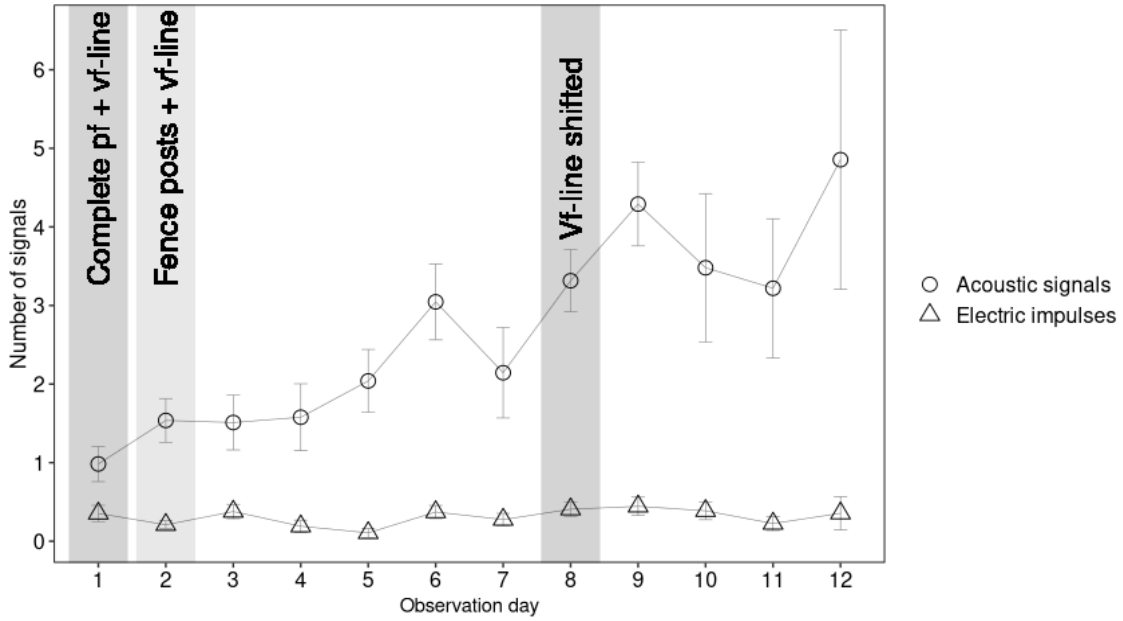


Figure 2. Acoustic signals/electric impulses per hour per heifer per day (mean ± se)

Time budgets for grazing and lying/ruminating, as indices for animal welfare showed no significant differences between the groups. Grazing was the main activity (pf-group: 75 ± 16%; vf-group: 73 ± 17% mean ± se) per day and it was significantly affected ($P < 0.0001$) by day of the training/time of the day in both groups. Daily time budgets for lying/ruminating (pf-group: 11 ± 12 %; vf-group: 13 %) were also significantly affected ($P < 0.0001$) by day of the training/time of the day. These values were similar to those for night-sheltered cows investigated by Homburger *et al.* (2015), who reported that grazing accounted for 55-75% and resting for 14-33% of records. The lack of differences in observed behavioural time budgets between the vf- and pf-groups in our study seems to be an indication that the animals' well-being was not affected by the use of the vf-technology. Supporting cattle learning vf-technology with the visual cue in the first two days might have enhanced the decisions by cattle to reverse response, as crossing the vf-line was impossible at the beginning. If cattle failed to learn the association between acoustic signals and electrical impulse, their welfare could be compromised. This, however was not the case in this investigation as no heifer had exceeded the value of 4 electrical

impulses per day at the end of the study, which is regarded as a criterion for successful learning (Eftang & Boe 2019). All heifers learned to avoid the electrical impulse by reacting to the acoustic signal. It could be assumed that increasing number of acoustic signals during the study period (Figure 2) reflects the cattle's increased motivation to approach the vf-line because of the decreasing forage availability (for more details see Grinnell *et al*. (2021) in these Proceedings). Cattle were observed grazing near the vf-line until the last note of the melody before they turned away to avoid the electrical impulse. As assumed by Campbell *et al.* (2019), shifting the vf-line affected the number of interactions. Wilkinson *et al.* (2019) suggested that the typical error of GPS positioning could hamper the learning process because cattle might receive signals even though they were away from the vf-line. A few 'unlogical' signals could be observed, but after a short irritation cattle continued interacting with the acoustic signals in order to access grass that met their grazing preferences. Exclusion worked and the vf-system proved to be 100% effective, which was confirmed by visual observation.

## Conclusions

In the present study, training the cattle according to the described approach, divided into different learning sections, reliably avoided crossing the vf-line. Cattle behaviour at pasture was not affected by using the virtual fence system. Establishing the present training protocol and the experiences of this study are considered to support current and future research exploring the vf-technology and its promising possibilities.

## Acknowledgements

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# Assessing feed efficiency in grazing dairy cows through infrared thermography and behaviour sensors

Haak T.[1,2], Münger A.[1], Südekum K.-H.[2] and Schori F.[1]

*[1]Agroscope, Ruminant Research Group, Tioleyre 4, CH-1725 Posieux; [2]University of Bonn, Institute of Animal Science, Endenicher Allee 15, DE-53115 Bonn*

## Abstract

Genetic selection for feed efficiency is hindered by the cost and difficulty of measuring individual feed intake. The objective was to explore the use of phenotypic proxies, namely surface temperature (ST), rectal temperature (RT), feeding behaviour and physical activity, to predict feed efficiency variables, i.e. feed conversion efficiency (FCE) and residual feed intake (RFI), in grazing dairy cows. Two groups of 14 Holstein and 14 Swiss Fleckvieh dairy cows were investigated during two mid- and one late-lactation period. During 7-day measuring periods, feeding and rumination behaviour, activity and individual herbage intake using the n-alkane marker technique of each cow was recorded. The ST was recorded indoors, once for each measurement period after morning milking at multiple body locations with a thermal camera. Estimated average within-herd feed efficiency was 0.78 (*SD = 0.17)* for FCE and -1.18 (*SD = 1.96*) for RFI with no significant difference (*P > 0.05*) between the breeds. FCE and RFI were best explained by maximum right front feet ST ($R^2$ *= 0.34*) and time interval between 2 consecutive foot strikes ($R^2$ *= 0.17*), respectively. The relationships were weak to very modest; however, they might be further improved by including other features such as milk and blood variables.

**Keywords:** eating, rumination, behaviour, surface temperature, feed efficiency

## Introduction

Achieving greater feed efficiency is one possible approach to improve sustainability of dairy production. Genetic selection for feed efficiency is greatly limited by the high costs associated with individual feed intake measurements. Previous studies (Cantalapiedra-Hijar *et al.*, 2015; Decruyenaere *et al.*, 2015) have identified biomarkers for nutrient utilization that are easier to implement, less stressful for animals and less expensive. Temperature regulation and animal activity have been identified as important aspects of physiological variation that could affect feed efficiency in dairy animals (Herd and Arthur, 2009). The objective of the study was to explore the use of the biomarkers ST, RT, feeding behaviour and activity, to predict feed efficiency variables, namely FCE and RFI, in grazing dairy cows.

## Material and Methods

The study comprised two mid-lactation and one late-lactation experimental periods. Each entailed a 21-day adaption period and a 7-day measurement period. Per experimental period twenty-eight lactating dairy cows, approximately half of them primiparous, were grazed on established rotational pasture. The cows were evenly divided between the Swiss Fleckvieh and Swiss Holstein breeds. Individual herbage intake was estimated during grazing with the n-alkane double indicator technique (Rombach *et al.*, 2019), and if concentrate was supplemented it was registered individually through the automatic feeding station. Based on the individual intakes of cow's FCE, expressed as total dry matter intake/energy-corrected milk yield, and RFI, expressed as effective minus required total dry matter intake, were computed. The behavioural characteristics (e.g. rumination, bites and strides) were recorded throughout the measurement periods with a halter and pedometer (RumiWatch, Itin and Hoch GmbH, Liestal, Switzerland). The recorded data were processed using the evaluation software RumiWatch converter version 0.7.3.36.

Thermal images were recorded indoors, once before morning feeding, according to manufacturer's recommendations, with an infrared camera (FLIR T620, FLIR Systems Inc., Wilsonville, OR, USA). The camera measured the surface temperature of body parts of the cows via radiated heat. The evaluated anatomical regions for the ST were eyes, ears, head, cheeks, snout, ribs, flanks, limbs, udder and rear area. The RT of each animal was measured immediately after thermal imaging using a digital thermometer (SC 12, SCALA Electronic GmbH, Stahnsdorf, Germany). The recorded data (milk yield and composition, body weight, behaviour, activity, ST and RT) were averaged per cow and period, as

herbage intake was estimated per measurement period. The relationships between feed efficiency and ST, RT, feeding behaviour and physical activity were analysed with a linear model in R. Measurement period and breed were included in the model as fixed effects.

## Results and discussion

The RFI (*P = 0.19*) and FCE (*P = 0.10*) values were not different between breeds. However, considerable between-animal variations for FCE (0.78, *SD = 0.17*) and RFI (-1.18, *SD = 1.96*) were observed, which is in accordance with a previous study (Arndt *et al.*, 2015). The ST tended to be higher in efficient cows. According to Case *et al.* (2012), more efficient animals have a higher metabolic rate and therefore the extra excess heat is lost as radiant heat. The maximum ST of right front feet (23.8°C, *SD = 4.7*; $R^2$ = *0.34*) and the minimum cheek (24.9°C, *SD = 4.1*; $R^2$ = *0.14*) best explained the FCE and RFI, respectively. Feed efficiency could not or only very weakly be predicted with RT (37.7°C, *SD = 0.4*) at $R^2$ = *0.09* and $R^2$ = *0.00* for FCE and RFI, respectively.

Table 1. Prediction of feed efficiency of grazing primiparous and multiparous Swiss Holstein and Swiss Fleckvieh cows with behaviour, activity and thermal biomarkers

| | $R^2$ | | *P*-value | |
|---|---|---|---|---|
| Biomarker | FCE[1] | RFI[2] | Breed | Parity |
| Eating and rumination activities[3] | 0.30-0.31 | 0.10-0.13 | >0.05 | >0.05 |
| Locomotion activities[4] | 0.25-0.30 | 0.08-0.17 | >0.05 | >0.05 |
| Surface temperatures of body locations (°C)[5] | 0.26-0.34 | 0.06-0.14 | >0.05 | >0.05 |
| Rectal temperature (°C) | 0.09 | 0.00 | 0.94 | 0.13 |

[1] FCE = feed conversion efficiency, [2] RFI = residual feed intake

[3] Eating and rumination activities included elements such as eating, chewing, drinking and rumination

[4] Locomotion activities included elements such as walking, lying, standing and strides

[5] Surface temperatures of body locations were eyes, ears, head, cheeks, snout, ribs, flanks, limbs, udder and rear

Feeding behaviour makes an important contribution to the underlying variation in feed efficiency of cattle (Fitzsimons *et al.*, 2017). The amount of time spent grazing (605 minutes per day, *SD = 55*; $R^2$ = 0.30) and amount of time spent with other activities (355 minutes per day, *SD = 88*; $R^2$ = *0.17*)) excluding activities attributable to any ruminating, feed intake or drinking activity, best predicted FCE and RFI, respectively. This is in accordance with Kenny *et al.* (2018), as low feed efficient cattle spent proportionately more time eating than their high feed-efficient contemporaries. Physical activity contributes to energy consumption and is interconnected with feeding-related behaviour, especially under grazing conditions. In accordance with Kenny *et al.* (2018) the physical activity (e.g. walking) was higher in low feed-efficient compared with high feed-efficient cows. The FCE and RFI were best explained by the average duration (1679 ms per stride, *SD = 42.6*) of one stride of the leg ($R^2$ = *0.17* and $R^2$ = *0.30*, respectively). Based on our study, a more efficient cow (low RFI and FCE) would spend less time grazing, have cooler body extremities and a lower core temperature compared with a less efficient cow. Biological differences between more and less efficient dairy cows may be useful to select the most efficient animals.

## Conclusions

Feeding behaviour, ST, RT and physical activity were correlated with feed efficiency traits and thus indicate the potential for application of some of these measurements in the assessment of efficiency traits in dairy cows. The relationships observed so far were modest but might be improved by their combination and by including other characteristics such as milk and blood variables. Moreover, these findings open the possibility of considering alternative methods to assess feeding efficiency through biological and behavioural proxies.

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# Automated detection of grazing behaviour with a collar-based monitoring system

Schmeling L.[1,2], Thurner S.[1], Nicklas D.[3], Erhard M.[2] and Rauch E.[2]

*[1]Bavarian State Research Centre, Institute for Agricultural Engineering and Animal Husbandry, Vöttingerstr. 36, 85354 Freising, Germany; [2]LMU Munich, Faculty of Veterinary Medicine, Chair of Animal Welfare, Ethology, Animal Hygiene and Animal Husbandry, Veterinärstr. 13/R, 80539 Munich, Germany; [3]University of Bamberg, Faculty of Information Systems and Applied Computer Sciences, Chair of Mobile Systems, An der Weberei 5, Bamberg 96047, Germany*

## Abstract

Monitoring the health and welfare of dairy cows in grazing situations is time consuming. Most monitoring systems available on the market were developed for use with housed cattle and attain low accuracies when used on pasture. Changes in grazing behaviour may serve as an indicator for heat and also health issues. Recording the grazing behaviour automatically with a monitoring system enables a reliable detection of oestrus and early identification of health disorders, and it provides supporting information for managing pasture-based dairy farms. Therefore, in this study, different prediction models for the automated detection of grazing behaviour were evaluated. Eight dairy cows were equipped with a monitoring system containing a three-dimensional accelerometer and a gyroscope. Ground Truth data were obtained from labelled video recordings. A Random Forest prediction model trained on an orientation-independent feature set and a window size of 5 s without overlaps achieved the highest accuracy. This model detected grazing with a sensitivity, specificity, and accuracy of 91.8%, 92.7% and 92.2%, respectively. The model confused grazing with walking, and by walking while chewing. To obtain the total feeding time and to reduce the misclassification with walking (plus chewing), another model for the detection of chewing while standing and walking is needed.

**Keywords:** dairy cows, grazing, monitoring system, health monitoring

## Introduction

Grazing of dairy cows at pasture is gains importance as it is associated with various benefits for the animals' health and welfare (Flury *et al*., 2016; Hernandez-Mendo *et al*., 2007) and as the demand, e.g. from society, for improving the welfare of livestock is increasing. In grazing situations, visual monitoring of the health and welfare of dairy cows is time consuming. Increasing herd sizes impede the supervision of individual animals and complicates the herd and pasture management. Smart farming solutions like monitoring systems continuously record different behavioural patterns and their changes, providing useful information for the detection of oestrus (Holman *et al*., 2011), health disorders and challenges (Stangaferro *et al*., 2016), and supply the farmer with details for pasture and herd management. Besides other behavioural patterns, feeding behaviour is a useful indicator as it is influenced by oestrus, health disorders, and challenges like heat load. Zebari, Rutter & Bleach (2018) found reduced feeding times on the day of oestrus. In the study of Sprinkle *et al.* (2000) changes in daily grazing time were used for the detection of heat load in cattle. The variation in feeding behaviour can be used by monitoring systems. In order to predict grazing behaviour from the sensor data provided by a monitoring system, a suitable model has to be found. The goal of our study was to evaluate a model for the automated distinction between grazing and non-grazing behaviour of dairy cows aiming at developing a monitoring system for dairy cows with access to pasture.

## Materials and methods

Data collection was conducted in two rounds of two days each on a dairy farm in Upper Bavaria, Germany. Five (round 1) and eight (round 2) clinically healthy, multiparous dairy cows were equipped with the prototype of a monitoring system (Blaupunkt Telematics GmbH) attached to a collar. The system was located at the lower neck and contained a three-dimensional accelerometer and a gyroscope. Data were collected with a frequency of 10 Hz.

Average parity of the selected cows was 3.4 (± 0.5) in round 1 and 3.5 (± 1.2) in round 2. The cows were 227 (± 28) and 285 (± 40) days in milk (DIM) in the first and second round, respectively. The cows were

grazed full-time except for one hour around each milking at 0700 am and 0500 pm. For the collection of Ground Truth data, four cameras (GoPro HERO 5) were attached to tripods, placed around the herd in adequate distance to avoid disturbance and moved frequently to record the behaviour of the selected cows as continuously as possible. Following the observation, video data were labelled based on an ethogram (Table 1). The definition of grazing behaviour was based on that used by Nielsen (2013). Non-grazing behaviour included walking, standing, chewing and other behaviour.

Table 1. Ethogram for labelling of the behaviour observed by cameras.

| Behaviour | Definition |
|---|---|
| Grazing | The animal bites off grass, chews and swallows, and moves forward with a lowered head. From the first grip of grass to lifting the head higher than the carpal joint. |
| Walking | The animal moves forward at walking pace and makes two or more consecutive steps in one direction. |
| Standing | The body of the animal is supported by at least three limbs. |
| Chewing | The jaw of the animal is in chewing motion masticating grass. |
| Other | Lying, lying down, standing up, ruminating, social behaviour, exploratory behaviour, comfort behaviour |

The data sets (sensor data and labelled data) of three animals were used to train the prediction model. Random Forest, an orientation-independent feature set and a window size of 5 s without overlapping proved to achieve the highest accuracy in the development process.

The data sets of the remaining animals were used to evaluate the model. Model output and Ground Truth were compared second by second. Correctly identified grazing and non-grazing behaviour was defined as true positive (TP) and true negative (TN), respectively. Grazing behaviour that was classified as non-grazing by the model was defined as false negative (FN), non-grazing behaviour that was classified as grazing was defined as false positive (FP). Sensitivity, specificity, and accuracy were calculated.

## Results and discussion

In total, 102.39 h of sensor data with corresponding video data were available for the evaluation of the model. Due to differences in operation time, animals contributed different shares to the total time (7.97 h - 21.65 h). Total sensitivity, specificity and accuracy of the model were 91.8%, 92.7% and 92.2%. Accuracy per animal ranged from 89.6% to 95.7%.

4.51 h of grazing behaviour were falsely classified as non-grazing behaviour (FN). Non-grazing behaviour misclassified as grazing (FP) amounted to 3.65 h. False positive time was studied more closely for three animals. Most of the time, grazing was confused with walking while chewing (36.0%) and walking without chewing (25.4%).

Lower performance values were achieved by a model for the detection of grazing behaviour based on accelerometer data developed by Nielsen (2013). They used the same definition for grazing behaviour and a sampling frequency of 5 s (besides other sampling frequencies).

A model developed by Molfino *et al*. (2017) detected grazing behaviour with a higher sensitivity and specificity but the comparison between Ground Truth and model output was conducted at 1 min-intervals, regarding the dominant behaviour within the minute. In contrast to our definition, Molfino *et al*. (2017) included chewing with head up in grazing behaviour; this behaviour was the one most confused with grazing in our findings.

The misclassification of grazing with walking (plus chewing) could be based on the window size. Although, 5 s windows achieved the highest accuracy, grazing behaviour - as defined in our study - is interrupted by short sequences of walking (plus chewing). If the duration of those sequences is ≤ 5 s, a successful prediction is impossible with a window size of 5 s.

## Conclusions

Compared to other models included in monitoring systems for dairy cows, the evaluated model detected grazing with reasonable accuracy. To obtain total feeding time on the pasture, another model needs to be developed for detecting chewing while standing or walking, as those patterns are part of the foraging behaviour. Developing a model for chewing (while standing or walking) could also help with reducing the FP time of our model.

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# Using LiDAR derived Digital Terrain Models and field data to quantify riverbank erosion and nutrient loading rates

Hayes E.[1], Higgins S.[2], Geris J.[3] and Mullan D.[1]

*[1]Geography, School of Natural and Built Environment, Queen's University Belfast, Belfast, Northern Ireland, UK; [2]Agri Food and Biosciences Institute, Belfast, Northern Ireland, UK; [3]Northern Rivers Institute, School of Geosciences, University of Aberdeen, Aberdeen, Scotland, UK.*

## Abstract

Nutrient and sediment loss from agricultural land is one of the major contributing factors in declining water quality. This research aims to quantify sediment and nutrient loading rates due to riverbank erosion using airborne LiDAR and field-collected data for sites in the Blackwater catchment, Northern Ireland. Using 2014 and 2020 LiDAR Digital Terrain Models, image differencing was performed in ArcMap to determine volume changes in riverbank elevation to quantify erosion rates. This was supported by cores of bank material, which were collected in situ for analysis of bulk density and total extractable phosphorus to determine sediment and phosphorus loading rates. We conclude that LiDAR and the collection of basic field data represent an innovative means to quantify erosion and nutrient loading rates without needing intensive time-consuming field surveys.

**Keywords:** LiDAR, riverbank erosion, nutrient and sediment loading rates

## Introduction

Riverbank erosion is caused by many factors including climate, topography, and land use (Thoma *et al.,* 2005). As stream sediment and phosphorus in agricultural systems can originate from both fields and riverbanks, it is difficult to determine the proportions delivered from each of these sources. To manage these losses, it is vital that the dominant contributing source is known (Thoma *et al.,* 2005). Light Detection and Ranging (LiDAR) is useful for identifying erosion, as performed by Thoma *et al.* (2005) at a catchment scale ($km^2$), and facilitates a change in direction from in-field sampling studies. Few studies have, however, investigated this technique at a high spatial resolution alongside appropriate field data at the field scale. This research aims to quantify riverbank erosion, P, and sediment loading rates at four field-scale locations using LiDAR and the collection of field data. This will guide suitable management practices to help achieve the EU Water Framework Directive targets. Details of the four study sites are provided in Table 1. Earlier unpublished work at these sites revealed highly variable soil P content using gridded soil sampling (35 m grid) with these results interpolated in ArcGIS using kriging.

Table 1. Description for the four field sites in the Blackwater catchment.

| Site | Area covered by Riverbanks A and B ($m^2$) | Land Use | Length of Stream Channel (m) | Riverbank Vegetation Characteristics |
|---|---|---|---|---|
| 1 | A: 937 B:818 | Grazing & Silage | 364 | Grass |
| 2 | A:1452 B:1579 | Grazing & Silage | 462 | Grass & small shrubs (<0.5 m ht.) |
| 3 | A:1891 B:776 | Grazing & Silage | 525 | Grass & shrubs (<0.3 m ht.) |
| 4 | A:698 B:786 | Grazing | 339 | Grass & small trees (c. 1-2 m) |

## Materials and Methods

To calculate erosion, we compared airborne LiDAR processed as Digital Terrain Models (DTM) for 2014 and 2020 at the Blackwater catchment in Northern Ireland at an elevation accuracy of ±0.15 m. Three riverbank bulk density samples were collected per site on 18 August 2020 using aluminium rings with a volume of 222 $cm^3$. These were hammered into the bank face below the root mat of ground vegetation. Bulk density was determined by the methods of Cresswell and Hamilton (2002), with total extractable P determined using the Olsen P methodology (Olsen and Sommers, 1982).

To calculate annual erosion rates, sediment, and P loads in ArcMap, the volume change value was divided by six to give an average annual erosion rate (reflecting the six-year spacing between the LiDAR imagery). DTM datasets were clipped to the site boundaries before producing an image differenced raster (in the Z dimension) using the raster calculator function under the general expression of "2014 LiDAR Dataset – 2020 LiDAR Dataset". With this expression, positive values represented erosion and negative values indicated deposition. To refine this to specific bank areas, manual digitising was performed with bank widths based on site-specific knowledge. Clipping was performed to these zones on the differenced raster. Riverbanks were designated as Riverbank A (left bank) or B (right bank), allowing any differences in erosion to be investigated in terms of channel morphology. While Thoma *et al*. (2005) analysed net volume change, this work focused only on bank erosion and its release of sediment and nutrients. As such, the function of "extract by attributes" was used with an expression of "value > 0", removing any negative values of deposition from the differencing rasters. The rasters containing only positive erosion values were used in zonal statistics to calculate the total elevation differences across each bank. This summed value of volume change was divided by the bank's spatial extent to give an average change in elevation, which represents the average erosion rate. For average mass wasting rates, this value was multiplied by average bulk density, and to calculate the average annual input of sediment for the bank the average mass wasting rate was multiplied by the bank's spatial extent. Finally, to calculate the average annual inputs of total extractable P, the average input of sediment was multiplied by the average total extractable P concentration. All values were determined for each bank and then summed to give an overall average value per site.

## Results and discussion

Table 2 shows the annual erosion, P, and sediment loading rates for each site and their riverbanks. While these calculations are average annual rates, consideration must be made for the dynamic nature of rainfall and river flow and how this influences erosion. Site 1, 2, and 4 show low erosion rates, with evidence for site-specific variability such as Site 2 Riverbank A showing deposition, whereas Riverbank B indicates erosion. The average mass wasting of sediment shows variability between Sites 1, 2, and 4, with site 4 showing the greatest average erosion rate for these sites. This is due to livestock accessing this site's banks and causing sediment displacement. This can lead to higher nutrient loading through animal excretion directly into the waterway. Despite having the highest erosion and sediment loading rates, Site 4 does not have the highest P loading rates due to fewer nutrient hotspots in-field compared to the P inputs at Site 1, which had widespread soil P hotspots in-field.

Table 2. Average annual riverbank erosion, sediment, and phosphorus loading rates calculated for the four study sites.

| Field Site | Average Annual Erosion Rate (cm $yr^{-1}$) | Average Mass Wasting inputs of Sediment (kg $yr^{-1}$) | Average Total Extractable Phosphorus Inputs (mg $yr^{-1}$) |
|---|---|---|---|
| Site 1 | 1.80 | 1.92 | 53.23 |
| Site 1 Riverbank A | 1.40 | 1.54 | 42.55 |
| Site 1 Riverbank B | 0.40 | 0.38 | 10.68 |
| Site 2 | 0.20 | 0.35 | 7.62 |
| Site 2 Riverbank A | NA Deposition Occurring | NA Deposition Occurring | NA Deposition Occurring |
| Site 2 Riverbank B | 0.20 | 0.35 | 7.62 |
| Site 3 | 79.10 | 128.14 | 2930 |
| Site 3 Riverbank A | 50.20 | 103.68 | 2370 |
| Site 3 Riverbank B | 28.90 | 24.46 | 560 |
| Site 4 | 3.14 | 2.47 | 17.85 |
| Site 4 Riverbank A | 2.34 | 1.79 | 12.90 |
| Site 4 Riverbank B | 0.80 | 0.68 | 4.95 |

Site 3 previously showed largely optimum soil P index values in-field. However, this site experienced extensive annual bank erosion rates, significantly exceeding the rates at any other site. There is evidence of channel morphology concentrating erosion onto Riverbank A. This disparity is reflected in sediment and P loading rates, which exceed any other site. The total annual sediment release dwarfs

the other mass wasting values. In terms of P released, this exceeds the other sites, despite Site 3 showing the fewest P in-field hotspots from soil sampling. These high loading rates highlight the issues for achieving good water quality concerning bank erosion and the need for intervention at this site.

## Conclusions

In agricultural catchments, sediment and nutrients can originate from soil erosion/runoff or riverbanks, so it is important to understand these sources to manage waterways effectively. By using DTMs derived from LiDAR, severely eroding riverbanks can be identified, avoiding field intensive surveys. Our methodology can be applied in this regard to help achieve WFD targets. Riverbank sources are difficult to quantify due to the site-specific nature of erosion and deposition. The ability to calculate sediment and nutrient loading rates is important for determining the proportion of contributing source areas. Although there are limitations with the accuracy of LiDAR, particularly for heavily vegetated areas, no other survey method exists to determine mass wasting rates as efficiently. Furthermore, this methodology can be replicated at various spatial and temporal scales. LiDAR allows us to acquire information remotely, rapidly, and at a high degree of accuracy. Given the need to improve water quality, this potential affords innovative opportunities for targeted management strategies.

## Acknowledgements

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# Using GPS sensors to estimate automatically the time dairy cows spend on pasture

Fischer A., Charpentier C., Lonis W., Philibert A., Allain C. and Lebreton A.

*Institut de l'Elevage, 149 Rue de Bercy, F-75595 Paris, France*

## Abstract

Since 2007, use of the 'Pasture Milk' labelling specification has grown further in Europe. It requires the cows to spend a minimal duration on pasture. Our objective was to develop and test an algorithm that estimates the time dairy cows spend outside the barn (T-Out), through an automatic detection of the barn, using a clustering method analysing the data recorded by embedded GPS sensors. Eight Holstein cows were equipped with a GPS collar during 56 days while having free-access to pasture at least 10 h/d. The reference T-Out (T-Outref) was calculated with a RFID antenna at the building entrance. The classification of T-Out as more (or less) than 6 h/day of pasture, as required for the French 'Pasture Milk' specification, matched the classification given by the T-Outref for 100% of the data. No effect of the number of cows equipped with a sensor has been observed on the estimation of average T-Out. However, when too few cows are equipped, the estimation of the whole herd's T-Out will be biased because some cows tend to stay in the barn. The estimation of T-Out using GPS collars seems promising to objectify the 'Pasture Milk' specification.

**Keywords:** grazing time, geo-tracking, dairy cattle

## Introduction

Naturalness has been identified as a key request by citizens worldwide (Schuppli *et al.*, 2014; Cardoso *et al.*, 2016; Delanoue *et al.*, 2018) in terms of their expectations regarding dairy cattle production. There are also demands for more transparency about the way livestock are managed (Frewer *et al*., 2005). To counter a reduced consumption of dairy products, several actors within the dairy sector in Europe have developed a label which certifies that cows spend time outside the barn. A minimum daily and yearly duration of access to pastures with a minimal accessible land area, for a minimal percentage of the herd are required for this specification, which is highly variable across dairies. Its checking is based on audits and notes taken by farmers, and is therefore time-consuming. Our study aimed at developing an algorithm which estimates the time dairy cows spend outside the barn using geotracking-embedded sensors to automatize part of the specification checking.

## Materials and methods

The time spent outside (T-Out) the barn has been monitored during 56 d for 9 lactating Holstein dairy cows which were part of a herd of 70 Holstein cows at the experimental facility of the Chambre d'Agriculture at Derval (France). Cows had to stay in the barn for complementary ration feeding and animal care tasks in the evening for about 2.5 h, then stayed on pasture after milking until 8:00, and had free access between the barn and pasture thereafter. The nine cows were equipped both with a pedometer (Nedap, Netherlands) and a GPS mounted collar (Digitanimal, Spain). An antenna placed in the corridor between the barn and the exit to pastures recorded the passage of each cow equipped with the pedometer and was used to calculate the reference T-Out (T-Outref). The GPS position was emitted every 11 minutes using the Sigfox network. Only the days having at least 110 GPS data were kept for the analysis. Consequently only eight sensors out of the nine were kept for the analysis. An algorithm has been developed to automatically detect the barn, based on the hypothesis that the density of geotracking positions would be higher when cows are in the barn than on pasture. This clustering method was developed with the dbscan package (Hahsler et al., 2019) available in R. The geotracking positions which were detected outside the barn by this algorithm were kept to calculate the time spent outside (T-Out) as the number of GPS positions outside the barn multiplied by the mean delay between two successive GPS records. The quality of T-Out estimation was characterized with the estimation of the root mean squared error (RMSE), the coefficient of correlation of concordance, and the decomposition of RMSE within mean bias, slope bias and random bias. The ability of the algorithm to correctly identify days with at least 6 h of T-Out, which is the minimum required in the French

specification, was evaluated with the estimation of percentage of good predictions, by considering that the positivity is the detection of days with more than 6 h T-Out. We estimated T-Out for all combinations of sensors from 2 to 8 sensors. An ANOVA was performed to test whether the number of GPS affected the performance of the algorithm.

## Results and discussion

The average T-Out estimated with the algorithm was 647 min (+/- 188 min), which was 35 minutes less than the T-Outref. The coefficient of correlation of concordance was 0.96, which shows that the estimation strongly reflects T-Outref. The estimation of T-Out was achieved with a RMSE of 55 min (coefficient of variation of 8.5%; Figure 1A). The main application of this method will be to count the number of days with at least 6 h outside the barn. The developed algorithm was able to assign 100% of the monitored days for all cows in the right class, i.e. as below or at least equal to 6 h T-Out.

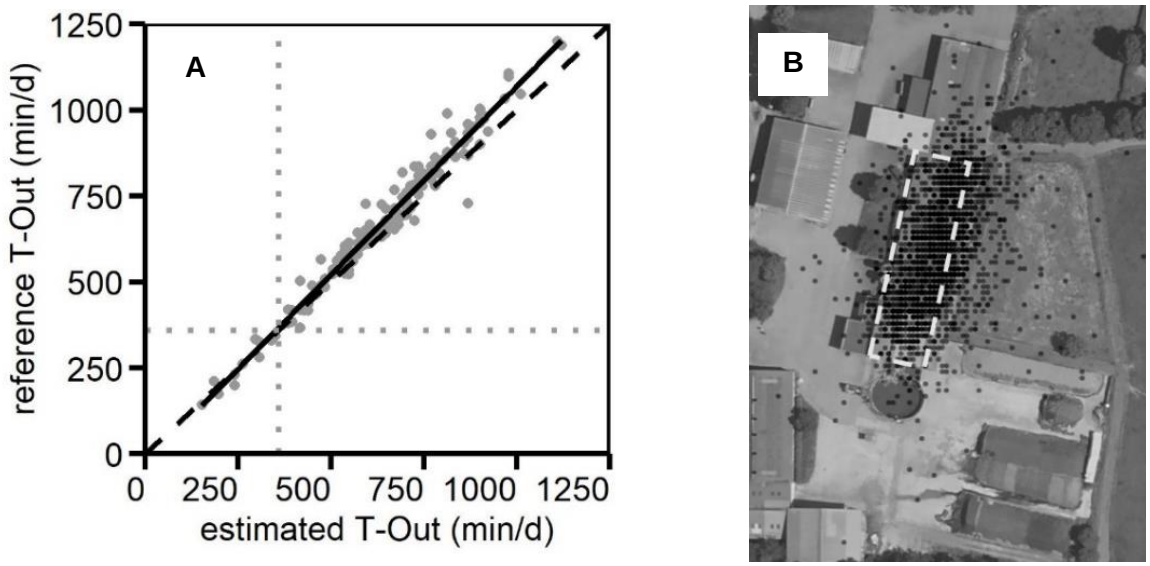


Figure 1. A: Relationship between the estimated and the reference time spent outdoors (T-Out; N = 171 observations). The black dashed line is the first bisector, the solid line is the linear regression (Y = -28.1 + 1.10 X, $R^2$ = 0.97). The dotted grey lines represent the 6 h threshold. B: Tracking of the 8 cows as recorded by their GPS sensors for the period when cows were locked in the barn. The white polygon delimits the barn.

The prediction error decomposition highlighted that the prediction error could easily be improved by reducing the underestimation observed when estimating T-Out with the algorithm. Indeed, 40% of RMSE was explained by a mean bias, which is explained by an underestimation of T-Out, especially for high T-Out (Figure 1A). The other 60% was split between random bias (49%), and slope bias (11%). Having an underestimation of T-Out, especially when cows spend less time in the barn, can be explained by an insufficient number of in-barn points for the algorithm to define the barn with accuracy. In addition, the accuracy of GPS sensors is lower in the barn. Indeed, several GPS positions were recorded outside the barn, while the cows were in the barn. A gap was seen between a cow's true position and the position recorded by GPS sensors when all cows were kept indoors (Figure 1B). The combination of both a lower accuracy of GPS when cows are in the barn and the shortness of the period within the barn contributes to a barn definition which is more impacted by GPS inaccuracy than the definition of the outdoor area. This may explain why there are cows grazing close to the barn but which were considered to be within the barn, and contributed to the underestimation of the T-Out. A solution could be to analyse the previous and subsequent GPS positions, as suggested by Bhattacharya *et al*. (2015).

The number of cows monitored with the GPS had no significant effect on the quality of barn detection because neither the surface nor the barycenter changed significantly with the number of sensors ($p > 0.05$). The average T-Out estimated over the whole grazing period did not significantly differ with the number of sensors ($p > 0.05$). However, we observed a relative increase of the frequency of having the minimum T-Out below the 6 h threshold when using fewer sensors. In fact, five cows had at least 2

days with a T-Outref below 6 h. If the specification requires that all days have a T-Ouest of at least 6h, we suggest either to increase the number of monitored cows or to choose cows that are representative of the whole herd. In a common system where all cows have either access to pasture or to the barn, but not both at the same time, one sensor will be enough. However, the need for sensors may be limited for the 'Pasture Milk' certification in those systems as T-Out estimation is obvious for farmers.

## Conclusions

A GPS embedded sensor combined with a clustering algorithm can be used to identify automatically the number of days dairy cows spend on pasture. Further steps are required prior to a commercial use, such as a validation on different systems and with more cows to have a more precise estimation of the absolute time spend outside by cows, as well as the estimation of the associated costs. Complementary applications such as grazing management and calendar, grassland use, heat and calving detection need to be developed to make the tool useful for farmers and be sure it will be used by farmers and not just to check the compliance with the 'Pasture Milk' specification.

## Acknowledgement

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# Use of drones with infrared cameras to search for fawns before mowing – experiences from practice

Mačuhová J., Wiesel T. and Thurner S.

*Bavarian State Research Centre for Agriculture, Institute for Agricultural Engineering and Animal Husbandry, Vöttinger Straße 36, D-85354 Freising, Germany*

## Abstract

First cuts of grassland and fodder crops coincide with the birth time of roe deer fawns. While older fawns on plots can escape from the mower, younger fawns lack the escape behaviour and can be injured or killed. The aim of the study was to collect the information such as detection success and labour input for detection of fawns before mowing by using drones with infrared cameras. The data were recorded by nine drone users during the season 2020. The searched area varied between 0.3 and 38 ha per plot with overall 581.4 ha on 161 plots. Fawns were found or seen on 48 plots. In total, 88 fawns were found (of which 40 could be caught) by search, 8 were seen and escaped during mowing, and 10 were found injured or killed during or after mowing. Field time (time from arrival until departure from the plot) needed per ha and team (2-5 people) to search the plots varied between 0.05 and 1.49 h (0.36±0.25 h; mean±SD). Most of the fawns could be found using the drones with infrared cameras. However, this did not enable all fawns to be rescued on mown plots.

**Keywords:** drone with infrared camera, detection, roe deer fawn, mowing

## Introduction

Most roe deer fawns in Central Europe are born in May and June (Rieck, 1955; Müri, 1999). Unfortunately, grassland and fodder crop fields are a popular bedding habitat for roe deer neonates (Jarnemo, 2002), and May-June is the time when first cuts are taken from grassland and fodder crops. Roe deer are long-term hiders, as the fawns hide motionless, odourless, with a reduced metabolic rate and secluded from their mothers most of the time during their first 6-8 weeks of life (Panzacchi *et al.*, 2009). It is only from the second to third week of life that the flight instinct replaces the hide instinct (Rieck, 1955). Therefore, they do not escape from mowers in the first weeks of life. Older fawns and even adult animals can also be injured or killed during mowing with high velocity (up to 16 km/h) and/or larger working width of mowers (up to 9 m or even larger). There are several methods to prevent fawns from being injured or killed during mowing. One possible method is to use drones with infrared cameras. However, less information is available about the success of the search and labour input by use of this method. The aim of this study was to collect information about the usage of drones with infrared cameras to save roe deer fawns before mowing.

## Materials and methods

Data recording was performed using an entry form in the season 2020. Data regarding technical equipment (type of drone and camera), flight settings, conditions during detection (e.g. temperature, type of vegetation, area of the plot, and crop height), arrival time at the plot, time of first and last flight, departure time from the plot, information about found or seen fawns, information about the use of additional methods applied to search the animals or scare them from plots before moving etc. should be recorded. One entry form was used for each plot. First data were recorded on 4 May 2020 and the latest on 3 July 2020.

## Results and discussion

Exact fawn numbers injured or killed every year during grassland and fodder crop cuts are unknown. In studies of Kittler (1979) and Kaluzinski (1982), the losses of roe deer fawns by mechanized agricultural operations were estimated at around 14.5% or even 26%, respectively. At present, there is increasing use of drones with infrared cameras to detect animals on the plots before mowing. In the present study, we received 161 evaluable entry forms from nine drone users, i.e. data from 161 plots searched with an area between 0.3 and 38.0 ha (3.61±5.41 ha (mean±SD)) and a total of 581.4 ha. Fawns were found or seen on 48 plots, and 88 fawns were thereby found (40 of which could be caught and placed i.e. under

or in a basket) by search with drone and infrared camera, 8 fawns were seen and escaped during mowing, and 10 fawns were found injured or killed during or after mowing. The exact reasons for presence of fawns on certain plot during mowing (i.e. after the search with drone) are unclear. A failed detection caused by technical problems and characteristics of grassland was noted as possible reason. Also, an incorrect decision of the drone pilot cannot be excluded. Furthermore, the impossibility of catching some fawns after detection seems to be one reason. Experience shows that fawns which are not caught try to come back onto the plot in the time gap between the search and start of mowing.

The first fawns were found on 8 May 2020 and the last on 24 June 2020. In the study of Müri (1999), the middle day of fawn birth was 27 May. In our study, most of the fawns were found or seen in the period between 22 May and 08 June 2020 (Figure 1). As the season progressed, the number of found fawns that could be caught decreased. Whereas no fawns were found or seen during mowing in the first two periods, 8 fawns were seen escaping from the mower in the last period. In contrast, 5 fawns in each period were injured or killed during the first two periods, but none was injured or killed in the last period.

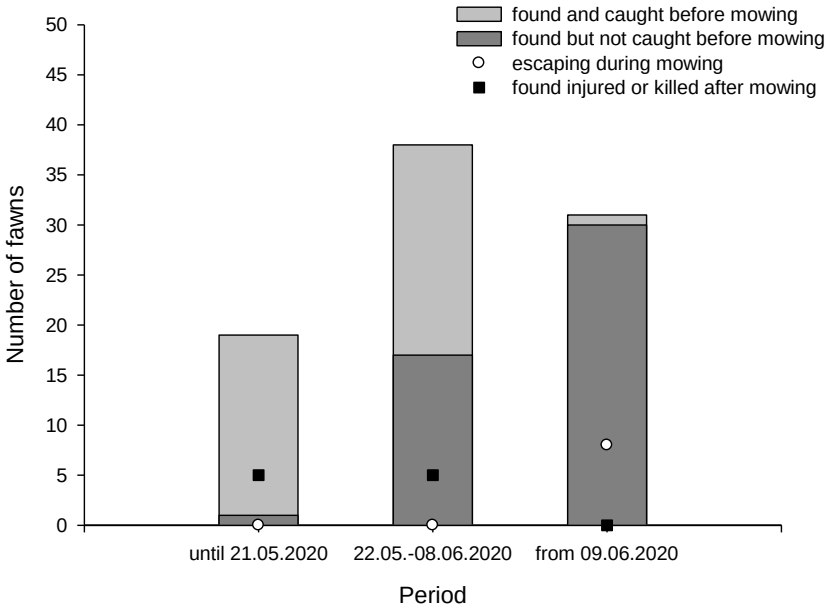


Figure 1. Number of found or seen fawns before, during or after mowing according to period.

Field time (time from arrival until departure from the plot; calculated from daily values per team, i.e. sum of all field times per team and day divided by sum of all plot areas per team and day) needed per ha and team (2-5 people) to search the plot varied between 0.05 and 1.49 h (0.36±0.25 h; mean±SD). Interestingly, there was no significant difference (*P>0.05*; Mann-Whitney rank sum test) in field time needed per ha and team (calculated from values per plot) between plots without and with finds (Table 2). However, the field time decreased with increasing plot area (Spearman correlation coefficient was -0.66 *(P<0.001)*). Moreover, the plot area without fawns (Table 1) was significantly lower (*P<0.001*; Mann-Whitney rank sum test) than plot area with fawns (1.6 and 3.0 ha per plot, respectively).

Table 1. Area of plots according to presence of fawns (i.e. found or seen fawns before, during or after mowing) on plot. [a,b] Values with different letters differ at the 5% level.

| | Plots | |
|---|---|---|
| Parameter | Without fawns | With fawns |
| Number of plots | 113 | 48 |
| Overall area of all plots (ha) | 324.7 | 256.9 |
| Average area of plots (ha; mean±SD (median)) | 2.87±4.30 (1.60)[a] | 5.35±7.14 (3.00)[b] |
| Minimum - maximum area of all plots searched (ha) | 0.3-38.0 | 0.3-30.0 |

Table 2. Field time per team needed to search the plot with drones with infrared cameras according to plots without or with fawn finds on plot during the search. [a,b] Values with different letters differ at the 5% level.

| | Plots | |
|---|---|---|
| Parameter | Without finds | With finds |
| Number of plots | 115 | 46 |
| Overall area of all plots (ha) | 337.5 | 243.9 |
| Average area of plots (ha; mean±SD (median)) | 2.93±4.31 (1.60)[a] | 5.30±7.26 (3.00)[b] |
| Minimum - maximum area of all plots searched (ha) | 0.3-38.0 | 0.3-30.0 |
| Field time for search per ha and team (h; mean±SD (median)) | 0.38±0.31 (0.31)[a] | 0.34±0.21 (0.33)[b] |

## Conclusions

Most of the fawns could be detected on the searched plots. However, even if the fawns were found, not all of them could be caught, and these were still in danger during mowing. Finally, 10 fawns were found injured or killed during or after mowing. Moreover, the time needed to search the plots using drones with infrared cameras should not be underestimated.

## Acknowledgements

Thanks to all drone users for the collection of the data. The study was supported by the Bavarian Ministry for Nutrition, Agriculture and Forestry under grant agreement no. A/19/17.

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# Testing the validity of a precision dairy ear sensor technology in recording grazing time

Grinnell N. A.[1], Hamidi D.[1], Riesch F.[1], Horn J.[1], Komainda M.[1], Ammer S.[2], Traulsen I.[2] and Isselstein J.[1]

*[1]University of Göttingen, Department of Crop Sciences, Grassland Science, Von-Siebold-Str. 8, D-37075 Göttingen; [2]University of Göttingen, Department of Animal Sciences, Albrecht-Thaer-Weg 3, D-37075 Göttingen*

## Abstract

Commercially available smart farming technologies, e.g. ear tags that collect behavioural patterns, claim to provide economic benefits to livestock production and improvements in animal welfare. As these technologies are mainly applied to confined systems, this study aimed to validate them by visual observations to investigate their suitability for grazed grassland. A total of 24 Simmental heifers were randomly assigned to six experimental groups. These groups were then assigned into two fencing-system treatments (virtual fencing vs. physical fencing) which were compared in three successive periods of 12 days each. An ear sensor (CowManager™, Harmelen, the Netherlands) providing information on cattle activity was attached to the animals before the start of the experiment. For each period, two groups of four animals were grazed in two 1000 $m^2$ paddocks and grazing behaviour was observed visually for 4 h daily. Data obtained from ear sensors on grazing activity were predicted from the data based on visual observations in a generalized least square model. The relationship between observation data and sensor data was significant ($P$<0.0012) with a root mean square error = 39.72 and $R^2_{adj}$ = 0.09. The ear sensor proved unreliable, and uncertainty in the prediction calls for further evaluation in the model.

**Keywords:** smart farming technology, ear sensor, sustainable livestock production, grazing cattle, pasture-based livestock production

## Introduction

Commercially available smart farming technologies claim to provide economic benefits to livestock production and to improve animal welfare. Previous studies have found precision dairy technologies to accurately predict and monitor dairy cow behaviour in confined dairy systems (Bikker *et al.*, 2014; Borchers *et al.*, 2016). While these technologies have, so far, mainly been tested and applied in confinement systems, circumstances may differ when animals have access to pasture. In grazing systems, changes in environmental and management conditions might cause a change in animal foraging behaviour. In a study investigating the suitability of ear sensor technology with grazing dairy cows, Pereira *et al.* (2018) found that sensors accurately monitored grazing and rumination behaviour but inaccurately depicted active behaviour. With the development of innovative animal control technologies such as virtual fencing, behavioural patterns may change, thus affecting the reliability of the ear sensor. So far, no study has investigated the effects of fencing systems on the reliability of predictions from ear sensors. Therefore, this study aimed to validate ear sensor technology with visual observations and to investigate their suitability for grazing systems with growing heifers on continuous pastures comparing two different fencing systems.

## Materials and methods

The study was approved by the animal welfare service of LAVES (Lower Saxony State Office for Consumer Protection and Food Safety - reference number: 33.19-42502-04-20 / 3388). The trial was conducted in August and September 2020 on the experimental farm of the University of Göttingen in Relliehausen, Germany with 24 heifers (Simmental, 462 ± 17.3 days age and 396 ± 32.7 kg live weight average) that were randomly assigned to six treatment groups. These groups were then assigned into two fencing system treatments (virtual vs. physical fencing) which were compared in three successive periods of 12 days each.

Visual observations were done to assess the effect of two fencing treatments on animal behaviour (Hamidi *et al*., 2021, in these Proceedings). Heifers were grazed five hours daily on adjoining paddocks

of 1000 $m^2$ size. The virtual fence groups were equipped with active, the physical-fence group with inactive Nofence collars (® Nofence, AS, Batnfjordsøra Norway). For training purposes, an exclusion zone was established within the paddocks with a virtual or physical fence line. Every group was observed continuously over four hours daily by the same persons resulting in a total entry of data observation endpoints of >69,000. Further, the animals were equipped with CowManager™ ear sensors (CowManager, Agis, Harmelen, the Netherlands) to monitor grazing activity. Data of visual observations were compared to recorded CowManager™ data from the same time frames. Using a generalized least squares model in R software, the total daily grazing time per animal in minutes $day^{-1}$ recorded by the sensors (DGTs) was regressed on the fixed effects of the grazing time recorded by visual observation (DGTo) and the fencing treatment effect, as well as their interaction.

## Results and discussion

Average DGTo was 181.7 ± 135.1 minutes, whereas average DGTs was 221.0 ± 81.8 minutes. The relationship between DGTs and DGTo was significant (*P*=0.0012) (Figure 1).

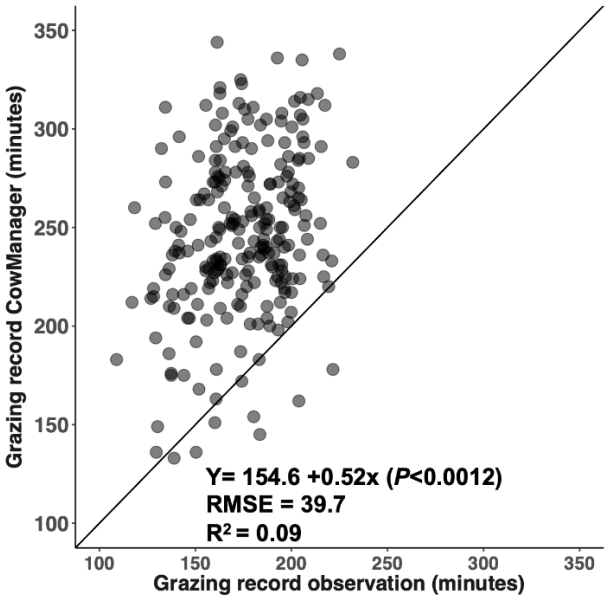


Figure 1. Relationship of daily grazing time (DGT) in minutes per observation day (4 h) recorded by CowManager™ sensors and visual observation of grazing heifers. The line shows the x y equal line.

Fencing treatment and the interaction between DGTo and treatment were not significant. Consequently, the fencing system did not affect the grazing behaviour, which is in line with Hamidi *et al.* (2021, in these Proceedings). However, the sensor data seem to overestimate the grazing time when compared to the observations (Figure 1) and the $R^2$ was fairly low ($R^2$=0.09). This deviation may be explained by the recording interval, as the internal sensor software aggregates data in minute intervals for each hour. Hence, the accuracy of the sensor will likely increase with a longer duration of one behavioural pattern. Visual observations were recorded in real-time, allowing intervals of < 1 minute. Grazing often occurs in motion, as the animal moves over the pasture (Hodgson, 1990), whereas in confinement systems animals typically eat in one spot, without moving. Thus, walking while eating may cause a discrepancy in the sensor records. Similarly, Pereira *et al.* (2018) found that sensors struggled to record active behaviour accurately. Further, visual observations included a more detailed set of behaviours (n=16) compared to the sensors (n=5) in smaller time units (<1 minute). Short disruptions of grazing, for social behaviour or vocal expression, would not be recorded by the sensor, potentially causing disparities in grazing time. As the heifers spent most of the observed time frame grazing, increasing the observation period and, thereby, grazing time could lead to the recording of more versatile behaviour, possibly increasing the sensor correctness. As other behaviour, such as lying or ruminating, is performed similarly in confined systems, sensor recordings can be expected to deviate less from visual observations than in the records of grazing behaviour. Thus, the investigation of other recorded activities from both sensors and observations will allow further in-depth evaluation of the sensor used.

Additionally, the poor correlation between sensor and observation data suggests the need for further analysis with optimized models.

## Conclusions

The study shows that virtual fencing technologies do not affect grazing behaviour of heifers. However, based on our study with 24 growing heifers, CowManager™ ear sensors are not suitable for the assessment of cattle grazing time, as short grazing periods might not be accurately depicted, and walking while grazing may be wrongly attributed in software outputs. Therefore, analysis with optimized models, of longer time periods and other recorded activities are necessary to further evaluate the sensor validity in recording animal behaviour in grazed grassland. Thus, it can be concluded that, so far, CowManager™ sensors insufficiently represent animal grazing behaviour and have limited suitability for recording animal behaviour in grazed grassland.

## Acknowledgments

We are grateful to Barbara Hohlmann and Eliana Mohn for supporting the fieldwork. Thanks to Knut Salzmann for supervising the livestock management. We thank Arne Oppermann for providing the grazing livestock and the experimental area. This study has been part of the project ‘GreenGrass’ funded by the German Federal Ministry of Education and Research.

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# Identifying areas of homogeneous grassland management based on iterative segmentation of Sentinel-1 and Sentinel-2 data

Wesemeyer M.[1], Schwieder M.[1,2], Pickert J.[3] and Hostert P.[1,4]

*[1]Humboldt-Universität zu Berlin, Geography Department, Unter den Linden 6, D-10099 Berlin, Germany; [2]Thünen Institut of Farm Economics, Bundesallee 63, D-38116 Braunschweig, Germany; [3]Leibniz Centre for Agricultural Landscape Research, Eberswalder Str. 84, 15374 Müncheberg, Germany; [4]Humboldt-Universität zu Berlin, Integrative Research Institute on Transformations of Human-Environment Systems - IRI THESys, Unter den Linden 6, D-10099 Berlin, Germany*

## Abstract

Remote sensing data in combination with image segmentation approaches have been shown to be valuable for identifying homogeneous areas such as agricultural land parcels. However, these approaches have not been widely explored for their usefulness in identifying homogeneous areas of grassland management under different management intensity levels. We present an unsupervised Bayesian segmentation approach for the combined analysis of Sentinel-1 and Sentinel-2 monthly composite data aiming to identify homogeneously managed grassland parcels, which was tested on an area of about 50 ha. We applied a segmentation refinement procedure with Sentinel-1 data in the first iteration and used Sentinel-2 data in the second iteration to delineate smaller areas within the identified segments. The approach led to promising results in intensively managed grassland areas with many mowing events. The results were also plausible under agriculturally extensive use. However, in semi-natural managed areas and in regions with varying environmental influences the identification of segments was prone to errors. The results show the potential of image segmentation in a grassland context, especially when management data are not available but needed. Our approach, although tested on a small scale, is applicable to larger regions.

**Keywords:** remote sensing, grassland management, time series, Sentinel-1, Sentinel-2

## Introduction

Mapping and monitoring of grassland areas are prerequisites, e.g., for informed management decisions, biodiversity assessments or agricultural statistics (Reinermann *et al.*, 2020). Spatially explicit information is lacking due to the extent of grasslands and the complexity of grassland management. Existing data like the Land Parcel Identification System do not reflect the complexity of grassland management, as differently managed parcels are often combined in one polygon. Remote sensing data in combination with image segmentation approaches have been shown to be valuable for identifying homogeneously managed areas such as agricultural parcels but have not been widely explored for their usefulness in identifying areas of grassland management. Since grassland management and use intensity are observable over time, we combined Sentinel time series data for our research.

## Data and methods

The study was carried out at the Paulinenaue research fields in Brandenburg, Germany (52°68´N, 12°72´E; 28.5 – 29.5 m a.s.l), for which detailed reference data were available. The chosen study area has a large variety of differently managed parcels with combinations of mowing and grazing in a comparably small area. The area is characterized by three management types: intensive (south eastern part), extensive (northern part) and semi natural (south western, south central). Parcels under intensive use (13, 16, 152, 171) are rather homogeneous in terms of management, fertilization, soil and water conditions and species composition after re-seeding the grass sward. Extensively used parcels (4-7) are also characterized by similar conditions but differ in their date and type of use (grazing or mowing events). The moist parcels under semi natural use (211-242) are characterized by varying soil and water conditions, are not fertilized and have an erratic grass species composition; number and date of use depended on natural growth (Figure 1). Parcels 91-102 are under semi-natural use as well and only mown.

We used an unsupervised Bayesian segmentation approach for the combined analysis of Sentinel-1 radar data (S-1) and Sentinel-2 optical data monthly composites (S-2) of enhanced vegetation indices

(EVI) both in 10m spatial resolution. The use of monthly composites enabled us to overcome limitations of both data domains (i.e., clouds in optical data, speckle in SAR) that were found to be problematic for the segmentation of large areas.

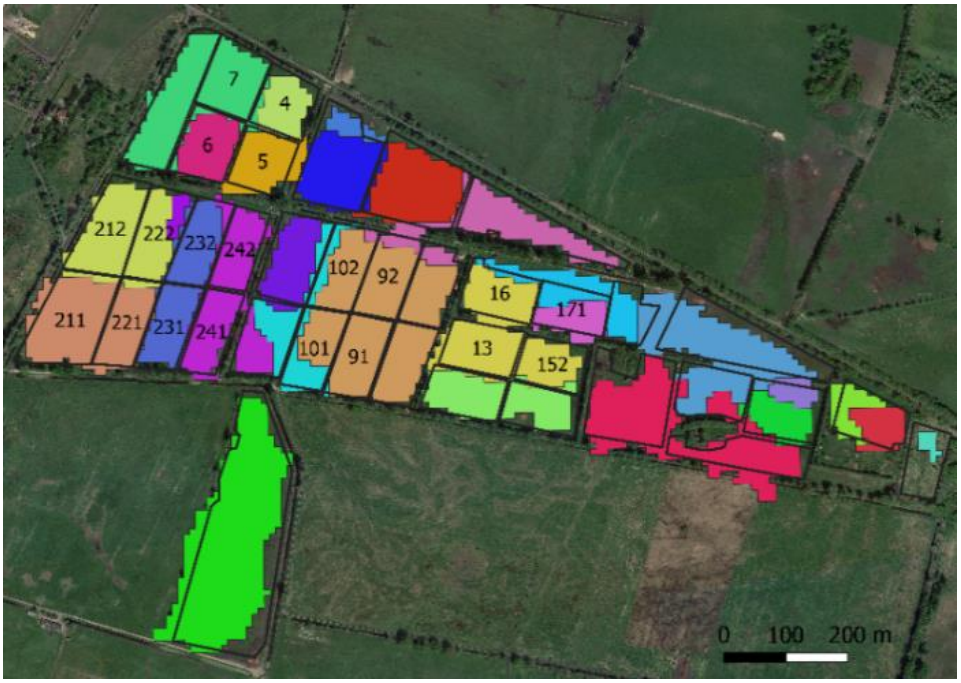


Figure 1. Segmentation results and reference areas.

The BaySeg algorithm (Wang *et al.*, 2019) is a Bayesian segmentation algorithm that considers proximity in feature space as well as in the spatial context. The dimension of space is modelled as a Markov-Random field (MRF), which is controlled by the beta coefficient, whereas smaller values represent a weak and higher values a high spatial constraint. Additionally, the maximum number of classes needs to be set, and neighbourhood definitions can be changed.

We adapted the algorithm to our problem and used the algorithm in three iterations, to assure that all areas of homogeneous management will be identified. In the first iteration the S-1 data were used to segment large areas into smaller patches in which it is much less likely to have data gaps in the optical data, which were used to refine the segments in the second iteration. Finally, all segments above a pre-defined spatial threshold of 1 ha were refined in a third iteration using optical time series. Monthly composites were acquired for the months March to November 2018. While the S-2 EVI monthly composites were obtained using FORCE (Frantz, 2019), the S-1 composites were acquired from the code-de (https://code-de.org/) platform. To focus the analysis on grassland areas only, a pixel-based grassland mask was applied. We validated the results based on the reference data and calculated the intersection over union metric between the reference parcel and the corresponding segment. It is defined between 0 (no spatial similarity) and 1 (complete spatial match). We calculated the overall segmentation quality (OSQ), which is a spatially weighed average over all segments (Tetteh *et al.*, 2020).

## Results and discussion

The objective of our research was to identify homogeneously managed grassland areas. The proposed approach led to promising results in diversely managed grassland areas with a moderate OSQ of 0.48. The three neighbouring intensively used grazing land parcels in the south eastern part (16, 13, 152 in Figure 1) were correctly identified as one common segment due to their similar use intensity and environmental conditions, while the fourth meadow parcel was separated (171). The various extensively used parcels of the study area (Figure 1, green frame) were successfully identified by their management differences as individual parcels (4-7 in Figure 1). However, in semi-natural managed areas and in regions with varying soil and water conditions and mixed species occurrence (211-242), the identification of segments was prone to errors. This can be observed in the south western and particularly in the eastern parts of the study area.

In the south-western part sometimes two neighbouring parcels were falsely merged to one segment (e.g., 211 and 221, 212 and 222), while parcels 241 and 242 were merged correctly (also 91-102). As some parcels were managed similarly in 2018, our algorithm merged those. The algorithm also merged parcels with similar environmental conditions despite the different management. This can happen when the management signal is not pronounced enough. In this case adding more features (e.g. different indices, other spectral bands) might improve the segmentation result but increases computational demands, which can be problematic for large areas assessments.

## Conclusions

The results show the potential of image segmentation in a grassland context, and this allows the identification of homogeneously managed areas. The segmentation is fully unsupervised and thus no additional training data are necessary. The approach works well for intensively managed grassland areas with clear management signals. Even though small-scale differences in environmental conditions may influence the results, the identified segments can be beneficial for grassland use-intensity estimations, as they enable the investigator to overcome data gaps or noise in pixel-based time series analyses (e.g., speckle effects in S-1 data).

## Acknowledgements

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# Estimating grassland biomass from Sentinel 2 – a study on model transferability

Buddeberg M.[1], Schwieder M.[2,3], Orthofer A.[1], Kowalski K.[2], Pfoch K.[2], Hostert P.[1,4] and Bach H.[1]

*[1]Vista Remote Sensing in Geosciences GmbH, Gabelsbergerstraße 51, 80333 Munich, Germany; [2]Geography-Department, Humboldt-Universität Berlin, Unter den Linden 6, 10099 Berlin.;[3]Thünen Institute of Farm Economics, Bundesallee 63, 38116 Brunswick, Germany; [4]Integrative Research Institute on Transformations of Human-Environment Systems, IRI THESvs, Humboldt-Universität zu Berlin, Unter den Linden 6, 10099 Berlin, Germany*

## Abstract

Satellite-supported information services support farmers in a variety of ways to make management decisions. However, most satellite-based information services focus on arable land and are not yet available for grassland. An important aspect in the development of such information services is the correct derivation of green leaf area and aboveground dry biomass from satellite data. This derivation forms the technical basis for all subsequent analyses and management recommendations calculated by satellite-based information services. In a previous study, green leaf area and dry biomass were already successfully derived for a grassland site using two alternative modelling approaches – an empirical model based on random forest decision trees and the radiative transfer model SLC. For operational use in information services, transferability of the methods used in different areas is necessary. In this study we calculated DBM with both models and compared the results to DBM data provided by a combine harvester. The spatial heterogeneity within the fields was well captured by both models. Both models calculated significantly lower DBM than was measured with the combine harvester.

**Keywords:** dry biomass, yield estimation, Sentinel-2, radiative transfer model, random forest

## Introduction

Satellite-based information service support farmers with a wide range of information, such as site-specific fertilization, water demands and yield predictions. While satellite-based information services are available for arable crops, information on grassland is still scarce. Knowledge about the expected amount of dry biomass yield from meadows is very inaccurate or often lacking. This provides a challenge for farmers, as they can only assume the fertilization demand of their fields and lack information if they will have sufficient biomass growth on their grassland to cover their fodder needs for the following winter. Satellite-based information services could provide relevant information for farmers if estimates of grassland yields could be calculated. In a previous study we developed two approaches and compared their ability to estimate dry biomass (DBM) from a Sentinel-2 (S-2) scene for a test site in northern Germany (Schwieder *et al*., 2020). In the first approach an empirical model (EMP), based on a random forest, was trained with field data from the Ribbeck (Germany) test site and validated against an independent dataset before it was applied to the S-2 scene. The second approach includes deriving the green leaf area (GLA) with the radiative transfer model Soil-Leaf-Canopy (SLC) and then calculating DBM from the GLA using the crop-specific leaf mass per area (lma). In the previous study, both models were able to predict DBM with high accuracy. Robust provision of satellite-based information services requires that the models developed can be transferred to other sites, which was tested in this study.

## Materials and methods

To test the transferability of the developed approaches, both models were applied on three other meadows on a different test site. The new test site is located near Paplitz (52°15'40"N, 12°14'2"E), about 100 km south of Ribbeck, where the models were initially developed and validated (Schwieder *et al*., 2020). All three meadows were cut on 30 June 2019. For all three meadows it was the second cut of the year 2019. Harvest data from a John Deere forage fodder harvester were available. These data were corrected for moisture to derive dry biomass values and corrected for outliers in the data range using histogram analysis, as described in Bach *et al*., 2016. No calibration with weighing data could be performed since no weighing data were available. The reference data show very high values of DBM for a second cut. A cloud-free S-2 scene was acquired on 26 June 2019, four days before the meadows

were cut. The S-2 scene was pre-processed using the Vista imaging analysis chain (VIAs) (Niggemann *et al*., 2014). Pre-processing included detection of clouds and cloud shadows as well as geometric and atmospheric corrections. The DBM was then derived from the satellite scene with both models (EMP and SLC), without further site-specific model adjustments. The DBM predicted by both models were compared to the available reference data. The analysis included field-average DBM-values and pixel-wise comparisons as well as calculation of the relative Root Mean Square Error (rRMSE).

## Results and discussion

The comparison of the modelled DBM to the reference data showed similar trends in both models for the three fields, with a good fit in the largest field and moderate to low fits in the two smaller fields (Figure 1, where each dot represents a 10 m x 10 m pixel). For all fields the results of both models revealed the same spatial patterns as in the reference data (Figure 2).

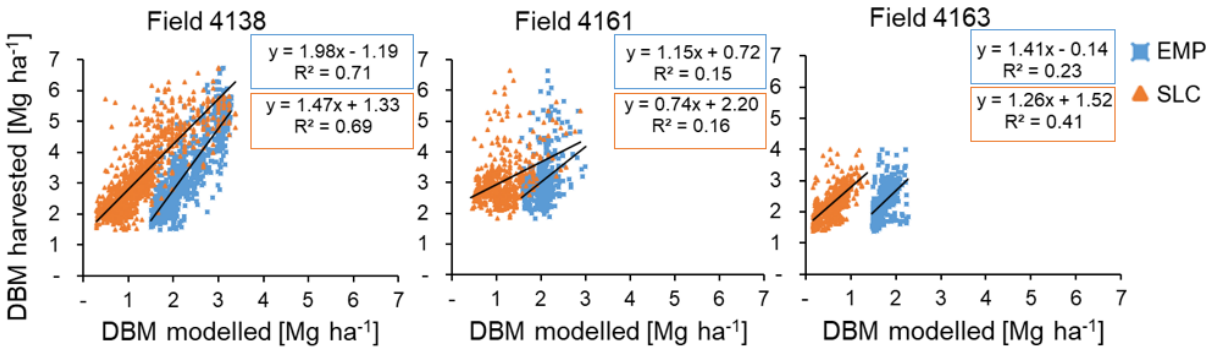


Figure 1. Pixel-wise comparison of model results to the harvest data provided by the forage harvester.

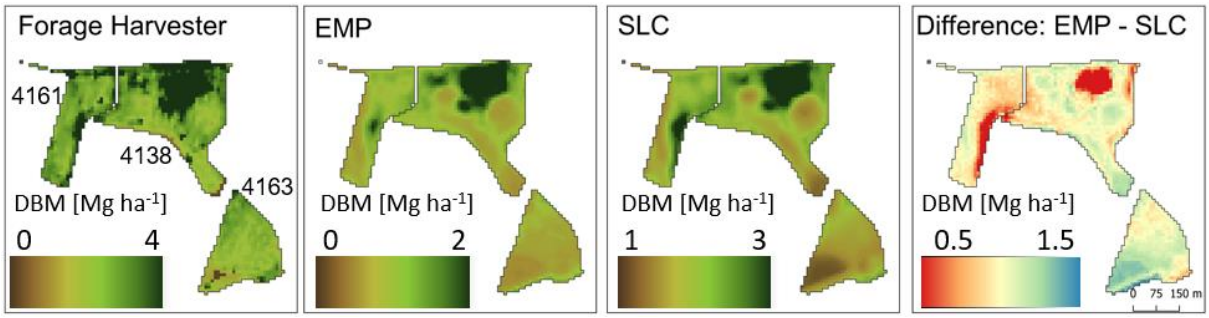


Figure 2. Maps of DBM measured by the forage harvester, calculated DBM results of both models and a difference map of the modelling results.

With regard to the average DBM per field, it was found that both models correctly reproduced the differences between the fields, but generally underestimated DBM (Table 1). DBM values modelled with EMP were generally higher than the results modelled by SLC.

Table 5. Overview of results on field average level.

| Field | Forage Harvester Data | SLC | | EMP | |
|---|---|---|---|---|---|
| No. | DBM [Mg ha$^{-1}$] | DBM [Mg ha$^{-1}$] | rRMSE [%] | DBM [Mg ha$^{-1}$] | rRMSE [%] |
| 4138 | 3.22 | 1.28 | 64.06 | 2.22 | 39.46 |
| 4161 | 3.03 | 1.12 | 67.12 | 2.00 | 41.18 |
| 4163 | 2.32 | 0.63 | 74.16 | 1.74 | 30.50 |

While both models were able to account for the spatial heterogeneity within the test fields, and they correctly represented the trends in DBM, the absolute values and subsequently the average DBM per field was underestimated by both modelling approaches. This partly contradicts the results of the study by Schwieder *et al*. (2020), in which the total amount of DBM was well estimated by both models when

compared to the reference data. While the management situation in both studies is comparable, differences in the modelling results might be caused by other influencing factors, such as different soil types, water availability or species composition.

However, a potential bias in the reference data used cannot be ruled out, as no weighing data were available to validate the combine harvester data and the reported average harvest amount of 3 Mg $ha^{-1}$ is at the upper limit for a grassland site managed with three to four cuts per year (Diepolder *et al*. 2016). The correct derivation of DBM with SLC is highly dependent on the assumed lma of the canopy, as the lma is highly variable and varies between different species as well as between years and cutting events (Poorter *et al*., 2009). Future research should therefore focus on the effects of species composition on the S-2 reflection signal and the variability of lma on different meadow types. Multi-temporal data could be used to assess lma changes throughout the growing period as a reaction to cutting events.

## Conclusions

The model transfer to an independent region showed that spatial patterns of DBM within and between fields can be estimated from multi-spectral S-2 data with both modelling approaches. However, the estimated absolute values did not match the reference data. Site-specific calibration (e.g., with harvest data) is thus still necessary to correctly determine leaf mass per area, and subsequently the DBM yields.

## Acknowledgements

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# Tools for information to farmers on grasslands yields under stressed conditions to support management practices – the GrasSAT project

Dąbrowska-Zielińska K.[1], Goliński P.[2], Jørgensen M.[3], Davids C.[4] and Persson T.[3]

*[1]Institute of Geodesy and Cartography (IGiK), Modzelewskiego 27, PL-02679 Warszawa, Poland; [2]Department of Grassland and Natural Landscape Sciences, Poznań University of Life Sciences (PULS), Dojazd 11, PL-60632 Poznań, Poland; [3]Norwegian Institute of Bioeconomy Research (NIBIO), P.O. Box. 115, NO-1431 Ås, Norway; [4]Norwegian Research Centre AS (NORCE), Nygårdsgaten 112, NO-5008 Bergen, Norway*

## Abstract

In order to manage grassland areas properly, and mitigate or avoid stress, precise information about grass growth conditions is needed. The main objective of the GrasSAT project is a fully operational system in the form of desktop and mobile applications, to provide a complementary tool for managing grassland production, mainly for medium and large farms in Poland and Norway. Combining the effectiveness of the application with the support of external advisers is the key to improve grass production management. The methodology for monitoring grass growth conditions and yield forecast will be based on synergistic use of remotely sensed data, process-based grassland models and reference in-situ data, indispensable for elaborating reliable models characterizing plant development. Using remote sensing to estimate the expected yield of a grassland site can help farmers to prepare for importing forage and to detect areas with high water stress. In addition, process-based models can help estimate the impact of a drought or freezing event on the yield. The project assumes the use of ground data for the calibration of satellite data.

**Keywords:** climate change, grassland production, remote sensing

## Introduction

Climate change is affecting grassland productivity across Europe (Kipling *et al*., 2016), e.g. in Poland as well as in North Norway. The extremes of weather in winter, i.e. often lack of snow cover together with low temperatures and frequent events of increased air temperatures early in spring, cause shifts in phenology and disturbance of the water balance in grassland areas. This may influence the grass yield. Also, lack of precipitation and increased temperatures later in spring and summer may cause water deficit or drought in some of the areas.

The project GrasSAT entitled “Tools for information to farmers on grasslands yields under stressed conditions to support management practices” will be conducted for a period of 36 months (Jun 2020-Jun 2023). The main objective of the GrasSAT project is a fully operational system in the form of desktop and mobile applications, to provide a complementary tool for managing grassland production, mainly for medium and large farms in Poland and Norway. The project-specific objectives were defined as follows: 1) delivery of a service in the form of desktop and mobile applications to optimize farm management like reducing the need for supplementary forage, and 2) development of a method for assessing grassland damage caused by drought or winterkill on the basis of multi-source satellite data and their synergy with meteorological data. Novel approaches will be based generally on innovative use of satellite data in the grassland management to increase yield and to monitor grassland status.

## Materials and methods

The overall scope of the work and the relations between the major research activities within the project are presented in Figure 1.

The reference data will comprise two types of information: in-situ measured soil-vegetation parameters and meteorological data. In Poland we will collect in-situ data on selected productive grasslands located mainly in dairy farms in two regions: north-eastern and central-western Poland. We will also select irrigated productive grasslands, which will allow us to compare the effect of artificial water supply on soil-vegetation parameters versus non-irrigated areas. In Norway, with winterkill as the main focus, test areas will be selected in the northern counties: Troms, Finnmark and Nordland. The in-situ data include

observations of the conditions of the fields, information on management, as well as measurements of grass yield, species composition and nutritive value. Meteorological data covering test areas, necessary for studying relationships between weather conditions and satellite-based indices, will be the second type of data.

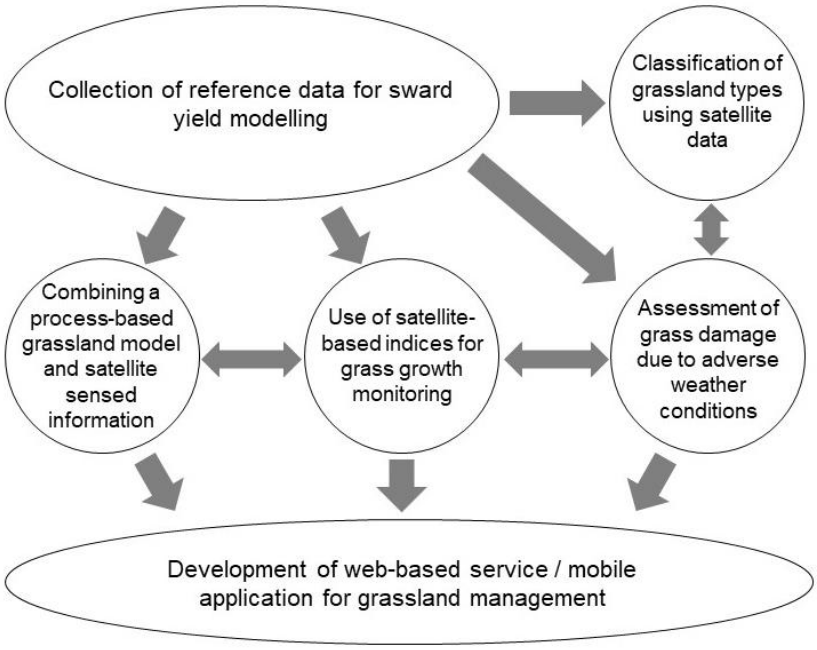


Figure 1. The major project activities and the relations between them.

For classification of grassland types a High Resolution Layer (HRL) provided by the Copernicus service will be applied, in order to delineate grassland areas for the selected test sites. Grassland areas will be extracted from Sentinel-2 images using masks prepared on the basis of the HRL layer. At the next stage of the work, various approaches to classification will be tested in order to determine those delivering the highest classification accuracy.

The relationship between the in-situ measured parameters (LAI, FAPAR, and biomass) and the indices derived from the satellite data (NDVI, EVI, NDWI) will be determined and subsequently used to predict vegetation parameters from Sentinel-2 and Landsat 8 data on a weekly basis during the growing season. This will be used to create maps of vegetation parameters (e.g. LAI) over the study areas. In addition, a model will be developed based on time series of vegetation indices during the growing season to predict yield at harvesting time.

The satellite-derived indices will be analysed with the meteorological data. To monitor and classify the drought areas, data from the Sentinel-1 satellite will additionally be applied to determine soil moisture variation. The already existing soil-moisture model developed at IGiK will be calibrated using a set of in-situ measurements (Dąbrowska-Zielińska *et al*., 2018). Determination of the winterkill conditions for grasslands will be based on Sentinel-2 and Sentinel-1 data.

In order to predict grassland yield and overwintering we will calibrate the Basic Grassland (BASGRA) model (Höglind *et al.*, 2020) against data obtained in GrasSAT. Model parameters will be calibrated against data derived from satellite information and/or in-situ registrations. Validation of the prediction accuracy of drought stress, winter survival/kill rate and biomass yield from the calibrated model versions will be conducted against independent in-situ registrations, or a combination of in-situ registrations and independently derived satellite data. The BASGRA model will then be applied to simulate and predict grassland performance such as winter survival for the current season.

Finally, we will create a website dedicated to presentation of project results, i.e. information on grass growth conditions, indications of areas affected with drought, winterkill and impacted by different

management, as well as the prognosis of grass yields. In parallel, the mobile application will be developed to deliver the same products to individual farmers.

## Discussion

Management practices well adapted to more variable and stressful environments are needed to maintain the agricultural productivity of grasslands in Poland and Norway in the future. The adaptation approaches to climate changes are grass varieties resistant to drought in central Poland (Kopecký *et al*., 2010) and to winterkill in northern Norway (Thorsen and Höglind, 2010), new strategies of grassland fertilization (Golińska *et al.*, 2016), soil moisture optimization by irrigation and/or drainage, use of variable cutting dates, and flexible grazing plans. It is therefore necessary to build new and efficient decision support systems, which provide a complementary tool for managing grassland production. This can help in planning for agricultural practices and offset financial risks at large scales.

## Acknowledgement

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# Accuracy improvement of Rising Plate Meter measurements to support management decisions in the Black Forest region

Stumpe C.[1], Werner J.[2] and Böttinger S.[1]

*[1]Institute of Agricultural Engineering, University of Hohenheim, Garbenstr. 9, DE-70599 Stuttgart, Germany; [2]Institute of Agricultural Sciences in the Tropics, University of Hohenheim, Fruwirthstr. 31, DE-70599 Stuttgart, Germany*

## Abstract

Yield monitoring during the growing season is of great importance for grassland farmers, but challenging so far. Grass yields are often estimated based on visual observations, especially in rural and small-scaled areas with extensive dairy farms like the Black Forest region. The Rising Plate Meter Grasshopper® (RPM) is a decision support system based on sensor technology which calculates available dry matter (DM) based on the measured compressed sward height. The accuracy of the calculation algorithm for the Black Forest region needs to be evaluated before the system can be used reliably. About 100 RPM measurements and corresponding herbage samples were taken at four test sites in the Black Forest region during the 2020 growing season. The results of the calculated DM based on the RPM-measurements show a mean deviation of 13% in comparison to the reference DM of the herbage samples. The accuracy can be improved by adapting the algorithm for this region.

**Keywords:** yield monitoring, extensive grasslands, decision support, sensor technology, rising plate meter

## Introduction

Sensor technologies promise benefits for farmers, animals and the environment in all parts of agricultural production. In grassland production these technologies have the potential to overcome the current challenges for farmers (Shalloo *et al*., 2018). For example, herbage yield determination in small-scaled regions is a recent issue. The usual estimations based on visual observations are not sufficient for precision grassland treatment and exact feed planning. Rising Plate Meters, like the Grasshopper®, are promising and relative inexpensive tools to determine the yield during the growing season and have been evaluated under different conditions. The Grasshopper® measures compressed sward height (CSH) precisely by using an ultrasonic sensor (McSweeney *et al*., 2019). Based on a standardized algorithm the system calculates the dry matter yield from the mean CSH. For intensive grasslands in Ireland the yield calculation based on this algorithm leads to relatively good results (O'Brien *et al*., 2019). In contrast, its application in Switzerland and Denmark has provided unsatisfactory results (Hart *et al*., 2019) and shows the need for system adaptation if used under conditions with non-intensive grasslands (Schori, 2020). Therefore, the objective of this study is the evaluation and adaptation of the Grasshopper® calculation algorithm for DM yield under the special conditions of grasslands in the Black Forest region of Germany.

## Materials and methods

The study was conducted on four grassland test sites near to Titisee-Neustadt in the Black Forest region. The test sites are managed by four different organic farmers. Following the method described by Klapp and Stählin according to Voigtländer and Voss (1979) the sward composition was determined and three different sward types (grass-rich, balanced and rich in clover or herbs) were classified. On each test site three test parts were spread over the area to represent the entire test site. The CSH of a 1 $m^2$ plot of every test part was measured by using the Grasshopper® once a week. The DM yield was calculated based on the standardized Grasshopper® algorithm considering a cutting height of 70 mm and a mean DM content of 21%. After the height measurement the plot was cut by hand at 70 mm and the cutting height was checked by using the Grasshopper®. Subsequently the fresh weight was determined, the samples were oven-dried at 60 °C for more than 48 hours and weighed in order to calculate DM yield and DM content as a reference value. During June and July 2020 a total of 99 data sets were captured. In order to compare the DM yield calculated by the Grasshopper® with the reference determined by the hand-cut samples, the values are plotted against each other (Figure 1). The accuracy of the system is

specified by the Root Mean Squared Error (RMSE) for the deviation of the calculated values from the reference values. In order to improve the calculation algorithm, the DM yield reference values are plotted as a function of the CSH and a regression analysis is conducted (Figure 2). The determined linear regression equation is subsequently used to adapt the Grasshopper® DM yield calculation.

## Results and discussion

The deviation between the calculated and reference DM yield is shown in Figure 1. Correct calculated values would fit on the broken line through the origin. The RMSE reflects the mean distance between the data points and the line through the origin. The accuracy quantification of the Grasshopper® by using the RMSE leads to a figure of 367.43 kg ha$^{-1}$. Thus, DM yield is calculated with a mean deviation of 13% related to the measurement range.

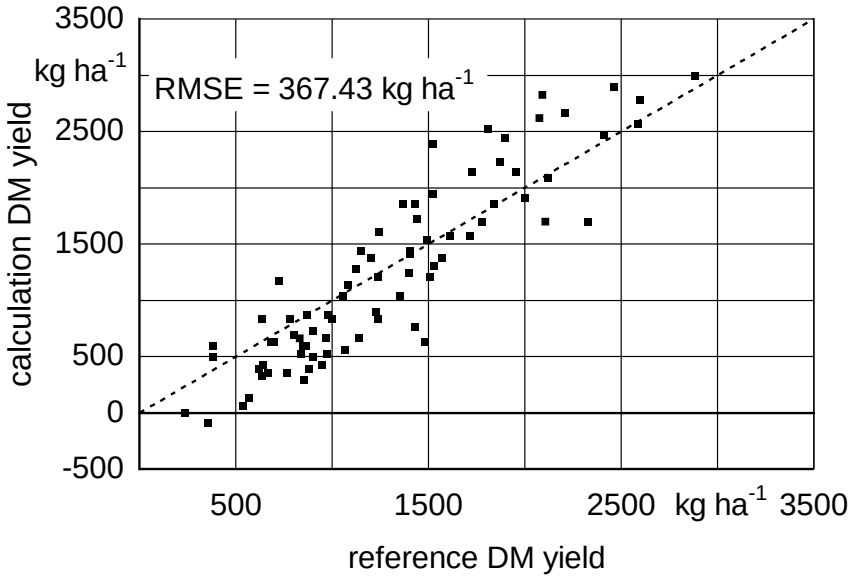


Figure 1. Calculated DM yield versus reference DM yield.

By plotting the reference DM yield over the CSH a strong correlation between these two values is shown (Figure 2). A regression analysis leads to a linear equation with a coefficient of determination of $R^2 = 0.826$. By using this linear equation as a basis for the Grasshopper® DM yield calculation from the CSH measurement, the accuracy of the calculated values can be enhanced. Thus, the RMSE value improves to 247.99 kg ha$^{-1}$, respectively 9.5% related to the measurement range.

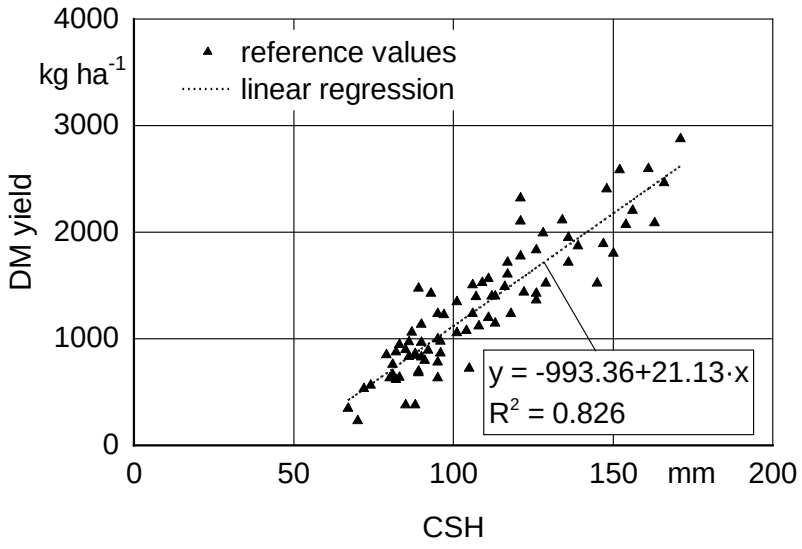


Figure 2. Reference DM yield versus CSH with linear regression line and coefficient of determination.

## Conclusions

The common Grasshopper® DM yield calculation based on the CSH measurement shows a deviation of 13% for extensive grasslands in the Black Forest region. The accuracy can be improved by the use of a region-specific conversion equation derived from regression analysis. Due to the Grasshopper® measurement technique and the heterogeneous grassland structure, a mean error of about 10% still remains.

## Acknowledgement

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# Botanical composition and progress of the growing season affect assessments of herbage yield based on compressed sward height

Peratoner G., Mittermair P. and Mairhofer F.

*Laimburg Research Centre, Vadena/Pfatten, I-39040 Ora/Auer, Italy*

## Abstract

Compressed sward height (CSH) measurements by means of rising plate meters are a standard management tool to assess the herbage on offer in pastures and can be used to quantify the herbage mass if a suitable calibration curve is available. In a field trial we explored the combined effect of CSH, vegetation type and progress of the growing season on herbage dry mass. Paired measurements of CSH by means of rising plate meter (Grasshopper®, True North Technologies, Shannon, IRL) and of herbage dry mass (harvest at 3 cm cutting height with electric scissors) were performed during the grazing season (end of April until mid-October) at three paddocks in the montane vegetation belt of the Alps (South Tyrol, NE Italy) managed by compartmented short sward grazing, and differing moderately in their botanical composition. General Linear Models accounting for the covariates CSH and progress of the growing season (expressed as day of the year), as well as for the vegetation type showed a significant effect of all factors. For an accurate prediction of herbage mass, a vegetation type-specific calibration, even with relatively similar vegetation types, seems to be useful.

**Keywords:** rising plate meter, herbage mass, seasonality, botanical composition

## Introduction

The measurement of the compressed sward height (CSH) by means of rising plate meters is a suitable tool for assessing the amount of herbage on offer on pastures, within a reasonable time and effort. Moreover, in heterogeneous swards, the large number of measurements allows a reliable picture of the variability in terms of herbage mass. However, the conversion of CSH measurements into herbage mass values requires calibration curves obtained for representative vegetation (Hart *et al.*, 2020). Moreover, the slope coefficient of the relationship between CSH and herbage mass has been shown to have a seasonal character (Ferraro *et al.*, 2012). In this paper the effect of both the botanical composition, with relatively small differences between intensively grazed swards, and of the advance of the growing season are investigated to produce a reliable estimate of the herbage mass based on CSH measurements.

## Materials and methods

The study took place at the experimental farm Mair am Hof (South Tyrol, NE Italy) at altitudes ranging between 890 and 930 m a.s.l., on three gently sloped, SSW-facing paddocks (Table 1) of about 1.4 ha each, all managed by compartmented short sward grazing from the end of March until the begin of November. Until 2017, the whole area of the paddocks was a homogenously managed ley. KRW1 had been resown in Autumn 2017 with a seed mixture containing *Lolium perenne*, *Poa pratensis* and *Trifolium repens* (37%, 55.6% and 7.4% seed weight respectively), whereas KRW2 and KRW3 were periodically oversown with the same seed mixture. Starting at the end of April, paired measurements of CSH by means of a rising plate meter (Grasshopper®, True North Technologies, Shannon, IRL) were taken twice per week until the end of the intensive grazing season (begin of October) alternately in one of the three paddocks at five spots chosen to cover the whole height range occurring at that moment. At the same spot where the grass height was measured, a grass sample was immediately taken within a 50 cm x 50 cm metal frame by means of electric scissors at a cutting height of 3 cm. For sward heights ≥ 8 cm, a round frame with the same size of the rising plate (40 cm diameter) was used instead. The reason for this round frame was that at high sward heights (usually corresponding with dung patches and refusals) the quadratic frame, having a larger area then the plate, usually included also vegetation with reduced herbage mass. The harvested herbage was then oven-dried at 60°C until weight constancy was achieved and weighed. The botanical composition in terms of yield proportion of all occurring species was assessed visually in each paddock within three randomly placed sampling areas of 100 m² during the spring growth phase (around mid-May) and again about one month later. Multiple regression

by means of General Linear Models was used to analyse the data. CSH and the progress of the growing season expressed as day of the year were treated as covariates, the paddock as a fixed effect. A stepwise forward model development was performed to fit the degree of the polynomials for CSH and progress of the growing season and to test for the interaction between the covariates. Only terms with $P<0.05$ were retained and the squared correlation between predicted and observed values and the Root Mean Squared Error (RMSE) were used to investigate the increase in prediction accuracy. Two third of the observations were used for training and one third for validation. The data was square root-transformed prior to analysis to achieve normal distribution of residuals and homoscedasticity. Multiple comparisons were performed by Least Significant Difference.

## Results and discussion

The botanical composition of the paddocks comprised a low number of species, ranging on average between 11 and 16 species (Table 1) and dominated by grasses with a yield proportion around 70%. However, there were some differences at species level. *Trifolium repens* was the only legume species and its proportion ranged between 7 and 24% (in KRW2 and KRW1 respectively, both on the late assessment date). A decreasing gradient for *Poa pratensis* from KRW1 to KRW3 and one for *Poa trivialis* in the opposite direction was apparent. *Dactylis glomerata* occurred with 9 to 16% in KRW2 and KRW3 only. The yield proportion of *Lolium perenne* was relatively constant, being on average around 25%.

Table 1. Location and botanical composition of the investigated paddocks. YPMS = percent yield proportion of species contributing up to 80% of the total yield. Dglo = *Dactylis glomerata*, Lper = *Lolium perenne*, Phpr = *Phleum pratense*, Popr = *Poa pratensis*, Ptri =*Poa trivialis*, Toff = *Taraxacum officinale,* Trep = *Trifolium repens*.

| Paddock code | Coordinates | Species number | YPMS on 13.05.2020 | YPMS on 10.06.2020 |
|---|---|---|---|---|
| KRW1 | 46°48'9'' N 11°57'26'' E | 11 | Popr (44%), Lper (26%), Trep (23%) | Popr (34%), Lper (28%), Trep (24%) |
| KRW2 | 46°48'12'' N 11°57'29'' E | 14 | Popr (29%), Lper (23%), Trep (13%), Dglo (11%), Ptri (8%) | Popr (27%), Lper (25%), Dglo (16%), Phpr (11%), Trep (7%) |
| KRW3 | 46°48'9'' N 11°57'34'' E | 16 | Ptri (28%), Trep (19%), Lper (17%), Dglo (9%), Toff (6%) | Lper (28%), Trep (14%), Toff (13%), Ptri (12%), Dglo (10%), Phpr (5%) |

The best fitted statistical predictive model of the herbage mass ($R^2$=0.796, *RMSE*=5.95) included two third-degree polynomials for both CSH and the progress of the growing season (Figure 1a). The progress of the growing season resulted initially, at a constant CSH, in increasing herbage mass values, followed by a decline and a second increase in the last part of the season (Figure 1b).

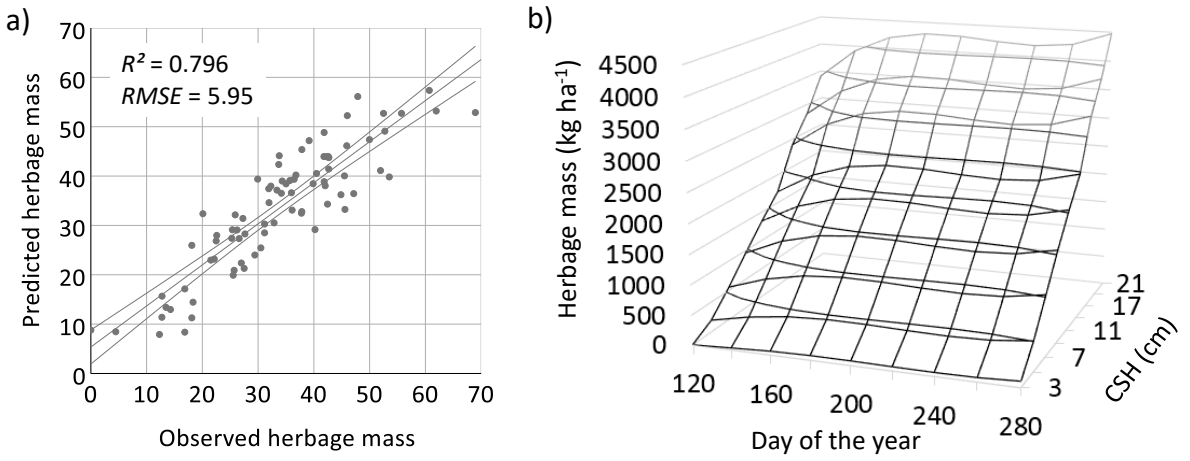


Figure 1. a) Observed vs. predicted herbage mass for the best fitted model (square root-transformed data) and b) predicted herbage mass value (back-transformed on the original scale) depending on CSH and progress of the growing season.

This pattern was more pronounced at high values of CSH. This effect may be due to the change from vegetative to reproductive growth of the dominant grasses and thus to the increased load bearing capacity of the stem material, affecting the relationship between sward height and herbage mass. These results resemble somehow the findings of Itano *et al.* (2012), who incorporated a periodic function in the estimation of herbage mass by means of rising plate measurements. All terms of the polynomials had $P<0.0001$, whilst the $P$-value of the paddock effect was 0.030. However, the effect of the paddocks was relatively small, with KRW2 showing on average slightly higher herbage mass than KRW1 and KRW3 (back-transformed values: 1350 kg vs. 1199 and 1164 kg $ha^{-1}$ respectively).

## Conclusions

Both the progress of the growing season and, to a lesser extent, the vegetation type of relatively similar swards allow improving the accuracy of statistical predictive models to estimate herbage mass depending on rising plate meter measurements. Even with relatively similar vegetation types, a vegetation type-specific calibration leads to an accuracy improvement when predicting herbage mass.

## Acknowledgement

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# Development of a digital tool adapted to pasture management in South-West Germany

Krug P., Weber J. F. and Elsäßer M.

*Agricultural Centre for cattle production, grassland management, dairy food, wildlife and fisheries Baden-Wuerttemberg (LAZBW), Aulendorf, Germany*

## Abstract

Grazing is a land use that has positive animal welfare benefits. A digital management tool called Weideinformationssystem ('Pasture Information System' in English), abbreviated as WIS, was developed to optimize grazing management. Farmers can integrate their list of individual animals as well as their list of fields currently managed for grazing into the WIS. The WIS can be used to document the number of grazing animals in the field each day to meet government funding programmes and to calculate the amount of nutrients excreted by grazing animals based on standardized values. Further development steps are planned to improve pasture management in order to generate benefits in terms of meeting the documentation obligations. It should be possible to integrate into the programme yield measurements and data on animal movement or grass intake, by various sensors, in order to evaluate the data and draw conclusions for optimizing grazing management.

**Keywords:** pasture, documentation, digital management

## Introduction

Within the framework of the Baden-Wuerttemberg (Germany) government-funding programme for agri-environment, climate protection and animal welfare (FAKT), financial compensation is paid to farmers for grazing of grassland fields with dairy cows and cattle over one year old. The farmer must document when each animal was on each field to ensure a minimum grazing period per animal. Until now, documentation has been done on paper by filling in a table with data for each day from June to September. In order to comply with the provisions of the fertilizer regulation, the farmer must also document the number of grazing animals and calculate the nutrient inputs for N, P and K for each field.

It should be possible to complete both types of documentation digitally in order to avoid having to enter data twice, and to enable further calculations to be performed with the data already entered. The digital application WIS was developed for these purposes.

## Materials and methods

In order to ensure that the application is practice-oriented from the outset, a committee of experts, including practitioners, was set up and is responsible for the technical design and content of the application.

The WIS was programmed for farmers to document the number of animals on a grazed field to meet the requirements of the government-funding programme and to calculate the amount of nutrients excreted by grazing animals, with average nutrient values for N, P and K based on standardized values under the fertilizer regulation. In addition to cattle, this is also possible for other animal species such as pigs, horses, sheep and goats. The system architecture of the application is shown in Figure 1. Company-specific data from HI-Tier (Zentrale Datenbank HI-Tier, München) and FIONA (Flächeninformation und Online-Antrag, MLR Stuttgart) serve as a database and can be imported into the application. The datasets to be used are displayed in the application and can be modified and supplemented. With the imported data, the user can make grazing entries in the application for each animal or group of animals (herds) as well as for each day and field. The processed data can be issued by the application in the form of as a pasture diary and a nutrient accumulation report.

## Results and discussion

A validation was performed by 60 farmers in Baden-Wuerttemberg to ensure functionality in practice. Feedback from farmers after the 2020 grazing period is used to improve the system.

It is very difficult to make a comparison with other systems, as there is no comparable system for southern Germany yet. Various field index providers such as ProFlura (ASSW GmbH CoKG, Tettnang) or 365FarmNet (365FarmNet GmbH, Berlin) offer the administration of grassland fields. Care measures, fertilization, cut uses and plant protection can be recorded. However, not all documentation possibilities are covered here, and grazing data are very difficult to collect in these programmes.

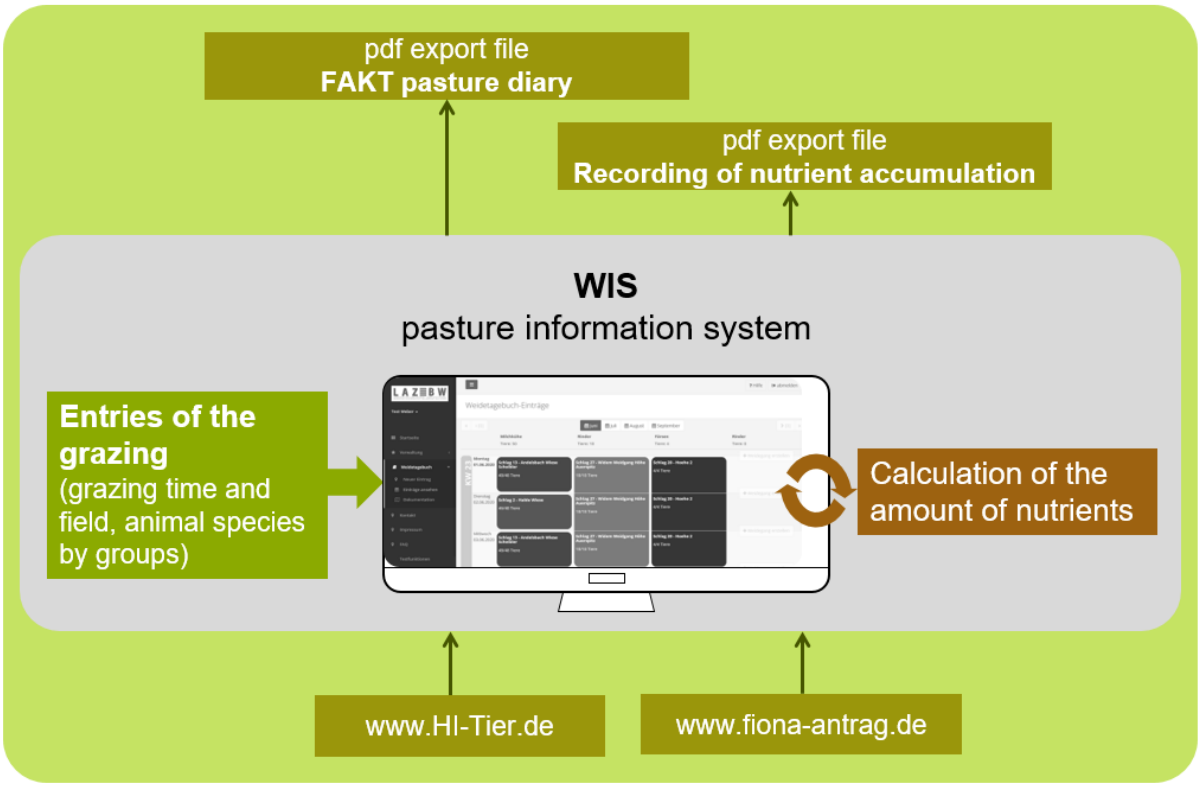


Figure 1. Schematic representation of the system architecture of the developed application WIS. Data about animals (www.HI-Tier.de) and fields (www.fiona-antrag.de) can be imported into the system. The user can make entries of the grazing and the system calculates the amount of nutrients and exports a pasture diary and a report of nutrient accumulation.

The company True North Technologies (Shannon, Ireland) has developed a pasture management system. Grass growth is recorded with a height measuring device (Grasshopper®) and transferred to an app and an online programme (www.grasslandtools.ie). The Irish user can see the yield of each pasture. By entering the number of grazing cattle and their daily fodder requirements, the online programme generates a forecast for the remaining grazing days and assist in pasture planning, but it does not record past grazing. However, ryegrass stands in Ireland cannot be compared with the heterogeneous grass stands in Baden-Wuerttemberg. Grass growth values can vary considerably due to specific local climatic conditions and differences in soil types and grass stands, as well as intensity of use.

Another grazing management support tool is Herb'Avenir (*Chambre Régionale d'Agriculture de Bretagne*, Rennes, France), which estimates the grass supply in days ahead. It also simulates the consequences of grassland management decisions on the grass supply for grazing and cutting for the following two months.

Currently, the WIS can only be used for the documentation of grazing activities. It does not include the recording of yield and feed intake of grazing animals. In later stages of development, yield estimation by altimeter, visual estimation, or similar methods could be included in the application. In addition, daily grass growth can be determined for regions in Baden-Württemberg. Due to the heterogeneity of grassland fields in southern Germany, it would be sensible to include other parameters such as stand type, season, water availability and temperature. The fodder available for a specific grazing period can

then be calculated. The calculated amount of fodder available and the needs of the animals allow the adjustment of the pasture management and the forecasting of the remaining grazing days.

A link with GPS technologies, as described by Thurner *et al*. (2012), could automate the documentation. The information for each animal could be automatically transferred into the application. Furthermore, a mobile version could be developed to optimize user-friendliness and to include the WIS in the farmer's workflow.

The special feature of the WIS is the support for pasture-based livestock farming, especially for small structured farms. It aims to promote sustainable grazing and to optimize pasture management in the future in order to make pasture-based livestock farming competitive. The great advantage for farmers is that the data about grazing for their own farm, which must be compiled for the documentation requirement, are already available in the WIS. These data are now available to calculate grazing fodder, stocking density and feed requirements. In this case, the user can greatly benefit from a compulsory documentation task and thus gain additional knowledge for his/her operational pasture management.

## Conclusions

The application makes it possible to combine individual farm animals with field data and grazing times for documentation (digital grazing diary). This documentation can be used for FAKT support and for the recording of nutrient inputs within the framework of fertilizer regulations. This digital tool can be used by small farm businesses. It is a programme that combines several targets, with the aim of promoting grazing and sustainable pasture management in Baden-Wuerttemberg.

## Acknowledgements

The WIS received funding from the Ministry for Rural Affairs and Consumer Protection of Baden-Wuerttemberg (MLR) and was developed by the Agricultural Centre for cattle production, grassland management, dairy food, wildlife and fisheries Baden-Wuerttemberg (LAZBW).

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