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

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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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