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REVIEW ARTICLE

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Remote sensing as a tool to assess botanical composition, structure, quantity and quality of temperate grasslands

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Abstract
Grassland systems frequently exhibit small-scale botanical and structural heterogeneity with pronounced spatio-temporal dynamics. These features present particular challenges for sensor applications, in addition to limitations posed by the high cost and low spatial resolution of many available remote-sensing (RS) systems. There has been little commercial application of RS for practical grassland farming. This article considers the developments in sensor performance, data analysis and modelling over recent decades, identifies significant advances in RS for grassland research and practice and reviews the most important sensor types and corresponding findings in research. Beside improvements of single sensor types, the development of systems with complementary sensors is seen as a very promising research area, and one that will help to overcome the limitations of single sensors and provide better information about grassland composition, yield and quality. From an agronomic point of view, thematic maps of farm fields are suggested as the central outcome of RS and data analysis. These maps could represent the relevant grassland features and constitute the basis for various farm management decisions at strategic, tactical and operational levels. The overarching goal will be to generate low cost, appropriate and timely information that can be provided to farmers to support their decision-making.

KEYWORDS
botanical monitoring, forage quality, grassland management, grassland yield

1 | INTRODUCTION

Traditional techniques based on field measurements (e.g., by cutting and weighing) are the most accurate methods for collecting data on herbage biomass (Frame, 1993). Obtaining a sufficient number of field measurements is a prerequisite for developing models and evaluating the estimation results. These approaches, however, are labour-intensive and time-consuming, particularly on sites that are remote or difficult to access, and they may be difficult to implement. They are also unable to represent variations in the spatial distribution of any biomass parameter over large areas. In these situations, remote sensing, with its repetitive data collection and digital format, allows fast recording and processing of large quantities of data, making it the primary source for estimation of biomass over large areas (Kumar, Sinha, Taylor, & Alqurashi, 2015; Rossini et al., 2012).

Remote sensing (RS) has been defined as "the field of study associated with extracting information about an object without coming into physical contact with it" (Schott, 2007). Within the present context, remote sensors are used to capture information about vegetation without necessarily making direct measurement of the parameters of interest, but simply by providing data from which the desired information can be extracted based on observed characteristics of the remotely viewed vegetation. Most sensors operate by integrating collected radiation over a sufficiently broad spectral range to achieve adequate sensitivity; that is, the captured signal is strong enough relative to the inherent noise level of the sensor.

The main advantages of remote sensing include the following: (i) the ability to obtain measurements from potentially every location in time and space, (ii) the speed with which remotely sensed data can be collected and processed, (iii) the relatively low cost of many remote-sensing data types and (iv) the ability to collect data easily even in areas which are normally difficult to access on the ground. Information collected by remote-sensing systems has different information features, such as the spectral, radiometric, spatial and temporal resolution, as well as the polarization and angularity (Barnsley, 1999). Many sensors used for biomass and quality estimation have different characteristics regarding spectral, spatial and temporal resolutions. Availability, efficiency and cost determine which sensor characteristics are appropriate for a given task (Kuenzer et al., 2014).

Recognizing and understanding the strengths and weaknesses of different types of sensor data are essential for selecting suitable methods for biomass estimation. Optical remote sensing, radio detection and ranging (Radar) and light detection and ranging (LIDAR) sensors provide the three main sources of remotely sensed data for biomass and quality estimation (Figure 1). Ultrasonic sensors also have an interesting potential usefulness.

There are vast areas covered by grassland and rangeland ecosystems in the tropics and subtropics, including savannas, and a large body of RS research has been conducted within these systems (Michelakis, Stuart, Lopez, Linares, & Woodhouse, 2014; Mutanga & Rugege, 2006; Paruelo et al., 2000; Sarrazin et al., 2011). Although this work has resulted in important methodological progress, many of the findings apply solely to the specific conditions of these ecosystems, and in most cases, they cannot be transferred to the grassland systems of moderate climates, which are typically managed more intensively. Thus, this review mainly covers studies that relate to grassland under moderate climatic conditions, although it also refers to work carried out in other climates when necessary.

In remotely sensed data, radiometric and atmospheric correction is an important requirement due to complex atmospheric conditions in time and space. There exists a wide range of methods to overcome these difficulties (e.g., Canty, Nielsen, & Schmidt, 2004; Du, Teillet, & Cihlar, 2002; Hadjimitsis, Clayton, & Hope, 2004; Heo & FitzHugh, 2000; Lu, Mausel, Brondizio, & Moran, 2002; McGovern, Holden, Ward, & Collins, 2002; Song, Woodcock, Seto, Lenney, & Macomber, 2001; Tokola, Löfman, & Erkkilä, 1999; Vermote, Tanre, Deuze, Herman, & Morcette, 1997). Topographic factors such as slope and aspect can affect remotely sensed data considerably, resulting in erroneous relationships between biomass and sensor data. Hence, removal of topographic effects on vegetation reflectance is essential and many approaches are available (e.g., Civco, 1989; Colby, 1991; Conese, Maracchi, & Maselli, 1993; Franklin,

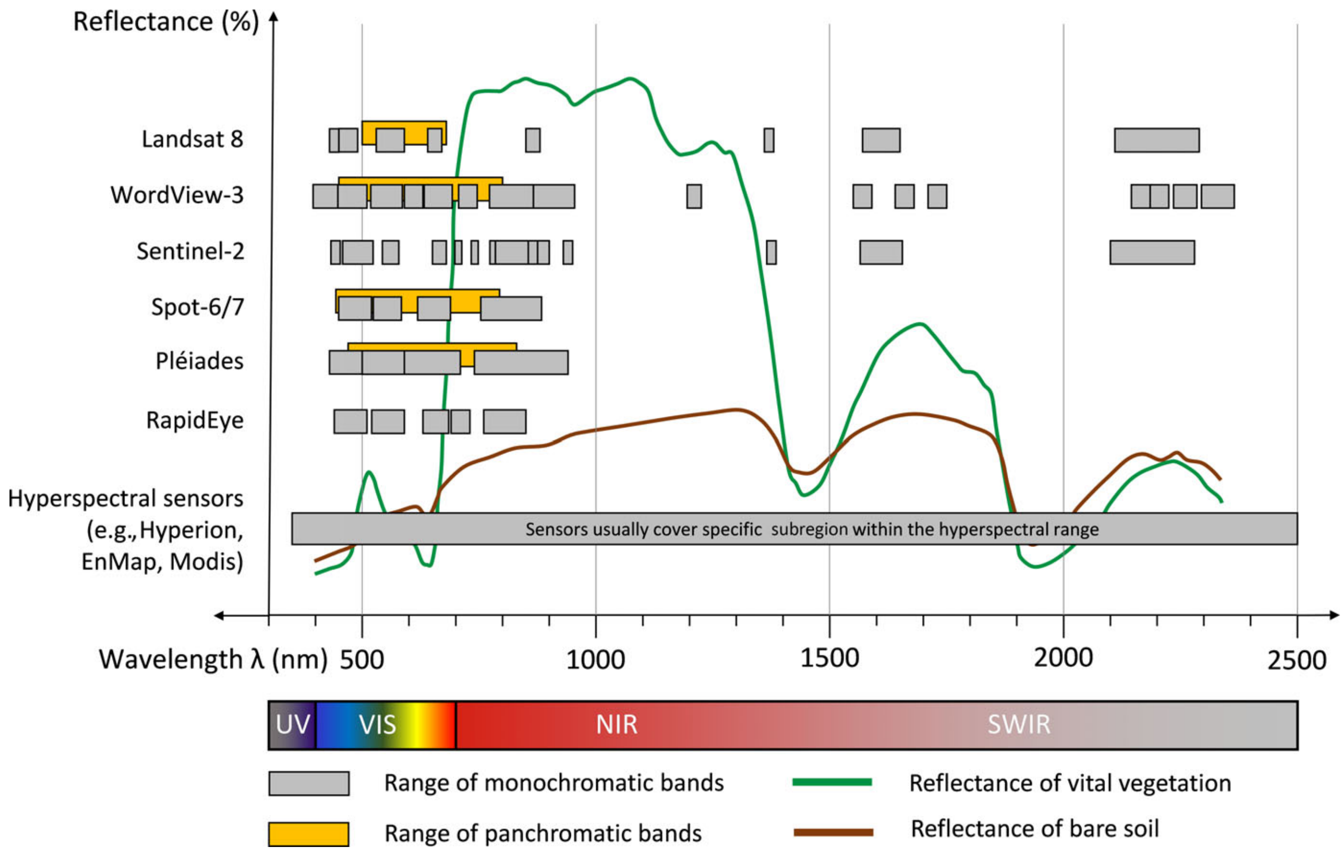

FIGURE 1 Band locations of selected multispectral earth observation satellites in comparison with the sensing range covered by hyperspectral sensors, which may also be mounted on a tripod, tractor or an unmanned aerial vehicle (UAV). UV, ultraviolet; VIS, visible; NIR, near infrared; SWIR, shortwave infrared

Connery, & Williams, 1994; Ricketts, Birnioe, Bryant, & Kimball, 1992). However, a detailed consideration of issues regarding data correction is not part of this review.

2 | SENSORS: TECHNICAL PRINCIPLES AND RECENT RESEARCH FINDINGS

2.1 | Photography

Photography creates durable images by recording electromagnetic radiation, either electronically by means of an image sensor, or chemically by means of a light-sensitive material such as photographic film. Film usually records radiation over a slightly broader wavelength range (0.3–0.9 μm) than that of the human eye (0.4–0.7 μm). In addition, more spatial detail can be seen on a photograph taken with the appropriate camera and film than can be observed with the unaided eye. Given appropriate ground reference data, accurate measurements of position, distance, direction, height, volume, area and slope can be obtained from photographs. Photogrammetry is the science of making measurements from photographs, especially for recovering the exact positions of surface points. A special case, called stereo-photogrammetry, involves estimating the three-dimensional coordinates of points on an object by employing measurements made in two or more photographic images taken from different positions. Nowadays, digital photography is the most used form of photography in remote sensing, which uses cameras containing arrays of electronic photodetectors to capture images focused by a lens, as opposed to an exposure on photographic film. The most common detector in digital cameras, a charge-coupled device image sensor, provides data in the blue, green and red areas of the visible spectrum.

Digital image analysis (DIA) and machine vision technologies have been successfully applied in agriculture to identify and estimate biomass and locate individual plants. For example, analysis of digital and photographic images has been used to estimate soya bean [*Glycine max* (L.) Merr.] canopy cover (Purcell, 2000), turfgrass cover (Richardson, Karcher, & Purcell, 2001) and biomass in semi-arid regions (Paruelo et al., 2000). DIA can be used to distinguish between crops and weed species (Hague, Tillett, & Wheeler, 2006; Onyango, Marchant, Grundy, Phelps, & Reader, 2005; Petry & Kühbauch, 1989). Sökefeld, Gerhards, Oebel, and Therburg (2007) used a bispectral camera to distinguish between plants and the soil background, as well as identify weed species and crop shape parameters, contour, and skeleton features to calculate a classification algorithm (Gerhards, Sökefeld, Timmermann, Kühbauch, & Williams, 2002; Nordmeyer, 2006; Weisa & Gerhards, 2007). The application of DIA to a heterogeneous grassland canopy may be more difficult than identifying plants against a uniform soil background, as is the case with arable crops. A canopy of diverse grassland plants presents several difficulties for DIA, including the diversity of optical plant properties within a mixed sward, varied leaf colours and shapes, overlapping of leaves and tillers, shadows on leaves and soil, non-uniform soil background and different leaf appearances during the growing season. Dock (*Rumex obtusifolius* L.) was detected in mixed grassland swards by recording images with a remote-controlled vehicle in the field, segmenting the images using a homogeneity threshold and defining objects and features by describing shape, colour and texture (Gebhardt & Kühbauch, 2007; Gebhardt, Schellberg, Lock, & Kühbauch, 2006). Bonesmo, Kaspersen, and Bakken (2004) developed an image processing system to estimate the canopy cover of white clover in a legume–grass mixture based on clover colour and morphological properties, and Fransen, de Boer, Terlou, During, and Dijkman (1998) used DIA to quantify the horizontal vegetation pattern in savanna grasslands. Based on results from a pot experiment, DIA was suggested as a method to assess the legume contribution in legume–grass mixtures (Himstedt, Fricke, & Wachendorf, 2009). A revised model was validated with weekly sampled data from spring, summer and autumn cuts of field-grown swards of red clover– and white clover–grass mixtures (Himstedt, Fricke, & Wachendorf, 2010). A high prediction accuracy (R^2 = 0.98, SE = 6% of DM) was obtained across a wide gradient of growth stages. Information from photographs is restricted to the canopy surface, however, and this may limit its applicability for tall-growing forage crops, like maize or cereals.

2.2 | Spectrometry

Spectroscopy makes use of electromagnetic radiation, which is normally in the wavelength range of 0.4–14 μm in wavelength, and measures the diffuse reflectance properties of vegetation, primarily with passive sensors. These sensors do not illuminate the scene (in contrast to, e.g., laser radars), but rather they rely completely on the sun's radiation. Vegetation is sensitive to electromagnetic radiation, with major absorption in the range of visible (72% of total energy absorbed by leaf pigments to support photosynthesis) and infrared radiation (50% of total energy absorbed through vegetation internal structure and water content). Healthy green vegetation typically shows a "peak-and-valley" pattern of spectral reflectance. In the visible spectral region (0.4–0.7 μm), valleys occur due to energy absorption by plant pigments both in the blue (chlorophyll b, carotenes) and in the red (chlorophyll a) bands, resulting in perception by the human eye of healthy plants as being green. As plants senesce or become subject to some form of stress, absorption in the blue and red bands is reduced and the plants are perceived as yellow, that is, a combination of green and red. Dying plants exhibit a brown colour, as leaf reflectance is decreased over the entire visible range. In the near-infrared range (0.7–1.1 μm), healthy plants reflect 40%–50% of the incident radiation and only 5% is absorbed, which is due to the internal structure of leaves. Shortwave infrared radiation (1.3–3 μm) is essentially absorbed or reflected depending on the water content and thickness of leaves.

While multispectral sensors measure the reflectance in 3–12 wide spectral bands, hyperspectral sensors acquire data in several hundred very narrow, contiguous spectral bands throughout the visible and NIR portions of the spectrum. Whether with terrestrial or air- and space-borne applications, the challenge of spectral analysis is always the same: to extract the meaningful quantitative spectral information from an image by filtering out background (e.g., soil), atmospheric (with air- or space-borne platforms) and instrument noise. The final result, that is, a mathematical model between canopy properties (e.g., yield, protein concentration, species diversity) and the full sensor system response, is referred to as spectrometer calibration.

Spectral sensors have raised considerable interest as a potential tool for prediction of the amount of biomass in pastures. Spectral reflection measurements have been widely used for the characterization of grassland biomass obtained from hand-held hyperspectral radiometers (Chen, Gu, Shen, Tang, & Matsushita, 2009; Mutanga & Skidmore, 2004; Kawamura et al., 2011; Vescovo et al., 2012), but may contain large amounts of redundant information. For practical implementation at field scale, the limitation of measurements to only the wavebands of relevant vegetation indices is desirable. Vegetation indices (VIs) are widely used in remote-sensing models for estimation of various crop characteristics (Hatfield & Prueger, 2010; Huang et al., 2012) including grassland biomass (Boschetti, Bocchi, & Brivio, 2007; Numata et al., 2007; Todd, Hoffer, & Milchunas, 1998). However, the performance of VIs is highly site- and sensor-specific (Huang, Turner, Dury, Wallis, & Foley, 2004). VIs based on NIR/red ratios, like the normalized difference vegetation index (NDVI), indicate saturation around a leaf area index of about 2.0–2.5 (Heege, Reusch, & Thiessen, 2008), which limits their applicability at higher biomass levels. Modifications have been made to reduce the saturation effects and the vulnerability to other environmental influences, like soil background scattering (Broge & Leblanc, 2001; Chen et al., 2009; Elvidge & Lyon, 1985; Huete, Jackson, & Post, 1985). Selection of distinctive narrow bands from hyperspectral data, for example, according to the NDVI-type formula, has shown improvements over traditional VIs (Inoue, Peñuelas, Miyata, & Mano, 2008; Reddersen, Fricke, & Wachendorf, 2014; Thenkabail, Smith, & de Pauw, 2000). There are difficulties, however, with biomass prediction at advanced developmental stages of grassland vegetation, as the ability of the reflectance sensor to detect canopy characteristics could be limited by the presence of a high fraction of senescent material in the biomass (Yang & Guo, 2014). Further limitations may originate from soil background effects (Boschetti et al., 2007), atmospheric conditions (Jackson & Huete, 1991), grazing impact (Duan et al., 2014) and heterogeneous canopy structures due to mixed species composition and a wide range of phenological stages (Biewer, Fricke, & Wachendorf, 2009a, 2009b).

For the assessment of forage quality parameters using proximal sensing of the pasture canopy, reflectance broadband multispectral sensors are considered to have limitations in providing accurate estimates of vegetation characteristics (Thenkabail, 2012). In comparison, hyperspectral sensors with narrow and near-continuous spectra allow much more detailed spectral information, offering significant improvements over broadband sensors. Partial least-squares regression (PLSR) is a technique for analysing hyperspectral data sets that employs the whole range of hyperspectral data in the analysis. Several studies have shown that PLSR is a powerful tool for the accurate prediction of elements of forage quality under field conditions (Biewer et al., 2009a, 2009b; Li, Mistele, Hu, Chen, & Schmidhalter, 2014; Starks, Coleman, & Phillips, 2004). Due to the cost and complexity of hyperspectral data, however, reducing the spectral data range and identification of the best spectral features of hyperspectral information is still the most important aim and this would facilitate simple sensor applications in the field (Biewer et al., 2009a, 2009b; Li et al., 2014; Reddersen et al., 2014). The authors suggest that hyperspectral data should be used to select the optimal wavebands for two-wavelength reflectance ratios. Comparisons show that traditional vegetation indices (VIs) (which commonly use average spectral information over predetermined broadband wavelengths) have a lower accuracy than hyperspectral narrowband VIs derived from hyperspectral measurements for various vegetation characteristics (Fricke & Wachendorf, 2013; Inoue et al., 2008; a; Möckel, Dalmayne, Schmid, Prentice, & Hall, 2016; Mutanga & Skidmore, 2004; Thenkabail et al., 2000). However, as selection of specific narrow wavelengths or reducing the hyperspectral range may lead to a loss of spectral information, combining spectral data with information from other sensors may be effective (see section 2.5).

2.3 | Spectral imaging

Spectral imaging is the combination of two different sensing modes: imaging and either multi- or hyperspectral spectrometry. Hyperspectral imaging sensors are able to capture simultaneously both the spatial and spectral content of remote scenes with high spatial and spectral resolution and coverage. The resulting data product is sometimes called a hypercube, which can be imagined as a three-dimensional data set in which each two-dimensional pixel contains a whole spectrum (representing the third dimension). The signatures of this spectrum are related to the materials being observed remotely. The size of each pixel depends on the mounting height of the scanner and its field of view and can vary between the subcentimetre range (with proximal measuring distance) and several metres (when the sensor is mounted on an aircraft or satellite). Table 1 displays the salient features of a variety of air- and spaceborne spectral sensor systems.

Several attempts have been made to estimate biomass in pastures and grassland using hyperspectral imagery, and most of them have shown generally good relationships between field data and remote-sensing-derived measures (Cho & Skidmore, 2009; Cho, Skidmore, Corsi, van Wieren, & Sobhan, 2007; Marsett et al., 2006; Schut et al., 2006). It is remarkable that most of the studies utilizing remotely sensed data for the estimation of grassland and rangeland biomass were conducted in tropical savannas (these ecosystems account for 30% of the primary production of all terrestrial vegetation) or in the semi-arid to arid rangelands of Asia or North America. In contrast, there are few comparable studies on grasslands in temperate climates (Kumar et al., 2015). Schut et al. (2006) used a hyperspectral imaging sensor system, which was mounted on a self-propelled vehicle and recorded reflexion intensity from 439 to 1680 nm. When predicting grassland yields on experimental fields,

TABLE 1 Parameters of air- and space-borne spectral sensor systems

Sensor system	Launch year	Altitude (km)	Revisit (day)	Spatial resolution (m)	Spectral coverage (μm)	Spectral resolution (nm)	Number of wavebands
Airborne							
HySpex[a]		Flexible	Any	Depending on altitude	0.4–2.5	3.26–5.45	470
AVIRIS[b]		Flexible	Any	Depending on altitude	0.4–2.5	10	210
Space-borne							
LANDSAT 8[c]	2013	705	16	15, 30, 100			11
Worldview 3[d]	2014	617	<1	0.31–30	0.4–1.75	Variable	28
Sentinel-2[e]	2015	786	5	10, 20, 60	0.49–2.19	Variable	22
SPOT 6/7[f]	2012/2014	694	1–3	2.2, 8.8	0.45–0.89	Variable	5
Pléiades 1A, 1B[g]	2011/2012	695	1	0.5, 2.0	0.47–0.94	Variable	5
RapidEye[h]	2008	630	1	6.5	0.44–0.85	Variable	5
EO-1 Hyperion[i]	2000	705	16	30	0.4–2.5	10	220
EnMAP[j]	2019	650	4/27	30	0.42–2.45	6.5/10	88/154
Modis[k]	1999/2002	705	1–2	250/500/1,000	0.4–14.4	Variable	2/5/29

[a]Norsk Elektro Optikk AS (2017).
[b]Jet Propulsion Laboratory (JPL) (2017).
[c]United States Geological Survey (2016).
[d]DigitalGlobe™ (2014).
[e]European Space Agency (ESA) (2017).
[f]Astrium - European Aeronautic Defence and Space (EADS) (2012).
[g]Airbus Intelligence (2014).
[h]planet.com – Planet Imagery – Product Specification (2017).
[i]U.S. Department of the Interior (2011).
[j]Deutsches Zentrum für Luft- und Raumfahrt (DLR) (2017).
[k]National Aeronautics and Space Administration (NASA) (2017).

they obtained R^2 values of 0.91, 0.86 and 0.96 for *Lolium perenne*-dominated, heterogeneous and grass–clover swards, respectively, with a root-mean-square error of 0.34, 0.48 and 0.17 t DM ha^{-1}. Application of the sensor system in the fields of two farms at several dates during the growing season produced larger errors of 1.4 t DM ha^{-1}, with a wide range in error among single dates. The authors attributed this phenomenon to system instability and environmental disturbances (effects of weather and location). Givens and Deaville (1999) reported similar problems of method incompatibility with infrared spectroscopy calibration set by three different consultants. Marsett found a strong relationship (R^2 = 0.77) between traditional biomass measurements and four band Landsat images from a variety of temperate to semi-arid grasslands of in the south-west of the United States. By applying the model to 23 upland grassland sites with collection dates over the course of 5 years, the estimated biomass values showed a strong relationship, with an R^2 of 0.96.

With close-range spectral imagery, Schut et al. (2006) obtained relative errors for N, P, and K contents between 6% and 12% when predicting quality of *Lolium perenne*-dominated, heterogeneous and grass–clover swards. For sugar concentration, relative errors were between 15% and 16%, and for crude fibre, neutral detergent fibre, acid detergent fibre and digestibility the relative errors were between 3% and 5%. Mutanga and Skidmore (2004) integrated continuum–removal absorption features from the visible, shortwave infrared and red-edge position derived from HyMap imagery and neural networks to map grass nitrogen concentration in an African savanna rangeland. This method obtained an R^2 = 0.92 with RMSE of 0.02% N for the training data set, whereas the test data set predicted only 60% of the variation in grass nitrogen (RMSE of 0.13% N). Mutanga and Kumar (2007) estimated and mapped the phosphorus concentration of grass in the same African rangeland with the same method and obtained a R^2 of 0.63 with RMSE of 0.07% *p* for the test data set.

The increasing ability of remote sensing to enable rapid delivery of data on habitat characteristics, including the distribution of individual plant species, habitat types and communities, and across a range of spatial resolutions and temporal frequencies, means that the use of remote-sensing technologies is becoming a necessity in conservation management (Mairota et al., 2015). Recent studies estimating diversity with remote-sensing techniques focused on mapping species distribution and alpha-diversity (Carter, Knapp, Anderson, Hoch, & Smith, 2005; Fava et al., 2010; Hall et al., 2010;

Psomas, Kneubühler, Huber, Itten, & Zimmermann, 2011). Rocchini et al. (2015) conclude that while the assessment of alpha-diversity is relatively straightforward, calculation of beta-diversity (variation in species composition between adjacent locations) is more challenging, making it difficult to estimate reliably the gamma-diversity (total diversity at the landscape or regional level). Following the spectral variation hypothesis, as proposed by Palmer, Earls, Hoagland, White, and Wohlgemuth (2002), several studies attempted to estimate alpha- and beta-diversity by relating the spectral variation of a site to the ecosystem heterogeneity at different spatial scales and in different habitat types (Möckel et al., 2016; Rocchini, Chiarucci, & Loiselle, 2004; Rocchini, He, Oldeland, Wesuls, & Neteler, 2010). The reasoning behind this approach is that environmental heterogeneity and high biological diversity are interconnected, because heterogeneous areas are likely to support more species due to a higher number of available ecological niches (Gaston, 2000). Limitations of this approach have been identified (Schmidtlein & Fassnacht, 2017), particularly related to coarse spatial grains. In an earlier study, Schmidtlein, Feilhauer, Bruelheide, and Rocchini (2012) developed a model using PLSR by regressing canopy reflectance against field data on the distribution of plant strategies according to the CSR model (competitive strategists, stress tolerators, ruderals) of Grime (1974, 1977). This model was then applied to airborne hyperspectral imagery on a per pixel basis. The resulting local maps demonstrate the potential to detect the composition of community strategy type. The maps also enable interpretation of plant species composition and environmental constraints. As the three plant strategies of CSR are related to the levels of productivity and disturbance at a given site, their change in space and time may serve as a measure of key processes such as succession, eutrophication and other changes in habitat conditions and may provide direct insights into the spatial ecology of a grassland area (Schmidtlein et al., 2012). In another application, reflectance values extracted from airborne hyperspectral imagery were regressed against Ellenberg indicator values for water supply, soil pH and soil fertility from montane rangelands (Schmidtlein, 2005). When applying the regression to the imagery, largely accurate maps could be produced giving the spatial distribution of soil attributes as indicated by Ellenberg values (R^2 = 0.58–0.68 in cross-validation), which makes them an appealing tool for vegetation monitoring.

2.4 | Synthetic aperture radar (SAR) and light detection and ranging (LIDAR)

In recent years, there has been increasing interest in synthetic aperture radar (SAR) data for aboveground biomass analyses, particularly in areas where frequent cloud conditions present difficulties for obtaining high-quality optical data (Erten, Lopez-Sanchez, Yuzugullu, & Hajnsek, 2016; Voormansik, Jagdhuber, Zalite, Noorma, & Hajnsek, 2016; Zalite, Antropov, Praks, Voormansik, & Noorma, 2016). The capability of radar systems to collect data in all weather and light conditions overcomes this issue. Furthermore, the SAR sensor can penetrate vegetation to different degrees and provides information on the amount and three-dimensional (3-D) distribution of structures within the vegetation. The basic operating principle of the radar system involves the transmittance of microwave energy (wavelengths within the approximate range of 1 mm to 1 m) from an antenna in very short bursts or pulses. Electronic measurement of the return time of signal echoes enables the distance between the transmitter and reflecting objects to be determined. Because of the complex manner in which radar signals interact with and return from features, the information content for a particular application varies considerably depending on slope orientation, surface roughness, vegetation cover and soil and vegetation water content. In general, shorter wavelengths (3–6 cm) are best for sensing crop canopies (Xianfeng et al., 2010). At these wavelengths, volume scattering predominates and surface scattering from the underlying soil is minimal. Vegetation with high moisture content returns more energy than dry vegetation, and more energy returns from crops when their rows are aligned in the azimuthal direction than when they are aligned in the range direction of radar sensing (Huang, Walker, Gao, Wu, & Monerris, 2016). Radar-based sensors are active and have a controlled power outlet, which ensures consistent transmission and return rates. Thus, the measurements of radar sensors are independent from solar radiation variations, unlike optical sensors (Erten et al., 2016). On the other hand, radar use has limited applications in regional or small-scale studies due to the small swath width, high costs of airborne acquisitions, lower sampling density of the large footprint waveform and the limited extent of coverage.

The two-dimensional (2-D) nature of optical remote-sensing data limits its use in direct quantification of some vegetation characteristics like canopy height and volume. LIDAR helps to overcome this limitation due to its ability to extend the spatial analysis to a third dimension. LIDAR, like radar, is an active remote-sensing technique. This technology uses pulses of laser light directed towards objects and measures the time required for the pulse to return to the sensor. The return time for each pulse is processed to calculate the distances between the sensor and the various objects. LIDAR systems have the ability to capture reflectance data from the returning pulses, in addition to the three-dimensional coordinates of the returns. Commercial LIDAR systems frequently utilize a rapidly pulsing laser (up to 70,000 pulses/s) with a near-infrared wavelength (1,064 μm). Such systems also allow measurement of the intensity of LIDAR echoes, which varies with the wavelength of the source energy and the composition of the material returning the incoming signal.

With the aim of monitoring grassland using multitemporal optical and radar satellite images, Dusseux, Corpetti, Hubert-Moy, and Corgne (2014) showed that SAR images enable better discrimination than optical images between grassland and crops in agricultural areas where cloud cover is very high for most of the time. The results show that the classification accuracy of SAR variables was higher than those using optical data (R^2 of 0.98 compared to 0.81). McNairn, Champagne, Shang, Holmstrom, and Reichert (2009) demonstrated that multitemporal SAR imagery could successfully classify crops for a variety of cropping systems present across

Canada. Overall accuracies of at least 85% were achieved, and most major crops were also classified with this level of accuracy. Several studies have established a strong correlation between LIDAR metrics and aboveground biomass. Most of these studies, however, were conducted in forests or savannas and in grasslands with substantial woody encroachment (Collins et al., 2009; Listopad et al., 2015; McGlinchy et al., 2014). Savanna and wood-encroached grasslands are characterized by an uneven distribution of vegetation biomass in 3-D space, with biomass allocated to above- and belowground components, as well as horizontal heterogeneity in the occurrence of an herbaceous layer with variable tree cover and open spaces. These structures differentiate these systems strongly from typical temperate grasslands, which are less heterogeneous and rarely show tree or shrub encroachment. Although LIDAR data have some advantages over optical data, there are a few issues that restrict its use for field applications. For example, LIDAR data analyses are complex and therefore require more image processing knowledge and skill, as well as specific software (Kumar et al., 2015). The LIDAR data acquisition process is expensive and covers smaller areas; hence, studies are still limited to specific areas and have not been applied extensively to larger areas for biomass estimation. Despite the popularity of radar and LIDAR data in forest biomass analyses, there are only a few studies in which such data have been utilized for the estimation of temperate grassland biomass (Wang et al., 2017; Zlinszky et al., 2015, Zlinszky et al., 2014).

2.5 | Ultrasound

Ultrasonic sensors determine the distance from an object by recording the time difference between the transmission of an ultrasonic signal (burst) and the reception of the signal's echo reflected by the object. Commercial sensors often utilize a one-headed system with one sonic transducer (frequency approx. 180 kHz) that acts both as transmitter and as receiver (Pepperl & Fuchs, 2017). The sensor automatically checks the reliability of the measurements and exports an output value according to the measured distance after a given response delay period. Hence, distance values are recorded at a frequency of about 5 Hz. Only the parts of the crop that are at a right angle to the ultrasonic beam can be detected as objects. The roughness of an object, together with the sensor-specific transducer frequency, determines whether the echo is reflected or diffused.

Ultrasonic sensors have been used since the late 1980s in tree canopy height and volume measurements (Lee et al., 2010). These sensors are widespread in process applications (Hauptmann, Lucklum, Püttmer, & Henning, 1998) and can provide high efficiency at a low cost (Park, Je, Lee, & Moon, 2010). Although the accuracy of modern ultrasonic sensors has improved, difficulties in interpreting the data often occur due to variance in measurement conditions and transducer behaviour (Henning, Prange, Dierks, & Daur, 2000). Across a biomass range of 0.35–2 t/ha in areas continuously stocked by sheep, measurements with an ultrasonic sensor underestimated sward height using top canopy heights as a reference. Despite this, biomass estimations were promising and had R^2-values between 0.66 and 0.81 (Hutchings, Phillips, & Dobson, 1990). Sonic reflections for ryegrass-dominated swards were weak, partly due to erect leaf orientation. The complex interaction between sward structure and reflection from the ultrasonic sensor is significantly affected by the size, angle and surfaces of leaves. Sensor-specific effects also play a role in this interaction (Hutchings, 1991, 1992). By installing an ultrasonic sensor on a tractor, Scotford and Miller (2004) were able to conduct on-the-go measurements of different winter wheat varieties with erect leaf canopies. Deviations between 4.6 and 7.2 cm from the reference crop height values were obtained. Reusch (2009) used a specific configuration of an ultrasonic sensor with an adapted control unit to estimate biomass in winter wheat. With this system, it was possible to retrieve multiple echoes from different leaf layers and the ground, and thus, the measurements were independent from the sensor's mount height. Forage mass–height relationships were evaluated by carrying out static ultrasonic measurements on binary legume–grass mixtures of white clover (*Trifolium repens* L.), red clover (*Trifolium pratense* L.) and lucerne (*Medicago sativa* L.) with perennial ryegrass (*Lolium perenne* L.) across a wide range of sward heights and forage masses (Fricke, Richter, & Wachendorf, 2011). A common calibration model for aboveground biomass including all sward types based on ultrasonic sward height explained 74.8% of the variance with a standard error (*SE*) of 1.05 t/ha. In contrast, in heterogeneous pastures, featuring a wide variation in species composition, phenological stage and sward architecture, ultrasonic recordings showed limited accuracy when correlated with grassland biomass (Möckel, Safari, Reddersen, Fricke, & Wachendorf, 2017).

3 | SENSOR COMBINATIONS

Most studies involving biomass estimation from remote-sensing data have used a single sensor or single-date image, which may not be sufficient for complex applications such as biomass estimation in heterogeneous areas or grasslands with high botanical and structural diversity. As remote-sensing data are available from a range of sensors, each with its own characteristics, a combination of sensors may be beneficial in terms of providing better information on the observed stand. Some information exists on the integration of multiple sensors for the estimation of aboveground biomass in forests. For example, the combination of spectral (data from Landsat TM) and spatial (radar data) information improved model performance for estimating forest area (Haack, Solomon, Bechdol, & Herold, 2002; Ban 2003).

In the case of grassland, however, there has been very little research on the benefits of sensor integration. Recent studies have shown that the fusion of optical and ultrasonic data resulted in an improved performance for biomass and quality estimation of highly heterogeneous pastures (Möckel et al., 2017; Safari, Fricke, & Wachendorf, 2016). Combining ultrasonic sward height data with narrow-band normalized spectral vegetation index (NDSI) or WorldView2 satellite broadbands (WV2) reduced the standard error of cross-validation (CV) for grassland biomass by up to 39% (Möckel et al., 2017), up to 37% for crude protein and up to 35% for acid detergent fibre (Safari et al., 2016) compared to the use of individual sensors. These estimations by these sensor combinations can be on a par or even better than estimations with the use of the full hyperspectral information. The prediction accuracy of biomass depends on the time of measurement. A study by Möckel et al. (2017) achieved the best results in the second half of the growing season. Narrow-band NDSI constructed with bands in these spectral regions may be preferred for research purposes where achieving the highest accuracy is essential, whereas WV2 provides interesting opportunities for practical applications, because these bands are already implemented on satellite platforms. The combination of ultrasonic and NDSI data increased the prediction accuracy of dry-matter yield of pure reed canary grass (*Phalaris arundinacea* L.) swards, grass-white clover swards and high diversity mixtures ($R^2_{cv} = 0.79$) compared to the independent use of these sensors (ultrasonic, $R^2_{cv} = 0.73$; NDSI, $R^2_{cv} = 0.38$) (Reddersen et al., 2014). In addition, the inclusion of leaf area index (LAI measured with a Licor LAI2000) in a triple sensor approach further improved the accuracy ($R^2_{cv} = 0.81$), which indicates that even dual sensor systems do not fully exploit the potentially available stand information. However, the presence of a high proportion of senesced material in pastures influences the performance of the sensor systems and may limit the applicability of such concepts in situations with advanced canopy age, for example, as occurs under management with low stocking rates. Thus, more advanced sensor systems are required to overcome the existing limitations.

4 | CURRENT AND POTENTIAL PRACTICAL APPLICATIONS

This section reports sensor-based applications, which are now commercially available for practical grassland management, but also discusses application, which may have a potential for future grassland management. Pastures from Space® offers services for regions in east and west Australia by combining NDVI images from the MODIS satellite (250 m spatial resolution) with current weather data to predict the pasture herbage growth rate (weekly values in kg DM ha^{-1} day^{-1}) and the amount of feed on offer (monthly values in kg DM ha^{-1}) (Mata, Henry, Gherardi, & Smith, 2004). Services were recently further expanded to include calculation of stocking rates, feed budgeting and fertilizer requirements using a comfortable user interface (Landgate, 2016).

Online sensing methods may provide prompt information about the current sward status regardless of weather conditions. “Pasture Reader XC1” is a sensor system developed in New Zealand that can be mounted on a tractor. It measures the sward height with an optical array of 18 light beams (C-Dax, 2016) at a high frequency (200 measurements per second) and at a speed of up to 20 km/hr (C-Dax, 2017). To assist with grazing management, data are directly transferred to a computer for calculation of the current feed wedge. In estimating the herbage mass of 5–16 cm high swards of variable plant composition, the prediction accuracy of the Pasture Reader XC1 ($R^2 = 0.77$, $SE = 0.311$ t DM ha^{-1}) was slightly lower than that of the conventional rising-plate meter (Schori, 2015). However, Pasture Reader XC1 measurements were taken about six times faster than those of the rising-plate meter.

Pasture Reader® (Naroaka Enterprises, 2017) is an online system which uses an ultrasonic distance sensor mounted on an all-terrain vehicle to predict grassland biomass from sward height measurements. By driving through the paddocks, the system calculates a mean value of the current biomass with a coefficient of determination between 0.78 and 0.91 at sward heights of up to 25 cm (Naroaka Enterprises, 2009).

While the Pasture Reader® is meant to replace the rising-plate meter (Sanderson, Rotz, Fultz, & Rayburn, 2001) as a rapid method to assess the current pasture biomass for stocking management, devices like GrassOmeter® (Monford, 2017) or Grasshopper (McSweeny, 2015) may provide alternative solutions. They are mounted on a boot or stick and measure the sward height while walking across the paddocks. Both devices use ultrasonic distance sensors and data are logged on the farmer’s mobile phone by an App and subsequently mapped in order to support paddock management decision-making. In contrast to the vehicle solutions, the speed of this system is comparable to that of the rising-plate meter.

Although at the present time there are only a few commercial RS applications in grassland, it can be expected that opportunities for new RS applications may open up in the future due to decreasing costs and increasing availability of sensors and sensor platforms (i.e., mainly UAVs). The increasing diversity in sensor techniques and configurations, as well as type and size of sensor-carrying platforms, will facilitate greater flexibility in the design of sensor systems to meet different requirements (e.g., spatial resolution, precision, measuring speed, payload and coverage area) for the fulfilment of tasks in both experimental and large farmland areas, where ground access may be difficult or time-consuming.

There have been numerous studies on sensor applications in arable cropping (Bredemeier & Schmidhalter, 2003; Lammel, Wollring, & Reusch, 2001; Weigert & Wagner, 2003), horticulture (Belasque, Gasparoto, & Marcassa, 2008; Dupont, Campenella, Seal, Willers, & Hood, 2000; Ushaa & Bhupinder Singh, 2013), viticulture (Baldy et al., 1996; Johnson et al., 1996; Lamb, Hall, & Louis, 2001) and fruit production (Ehsani & Karimi, 2010; Maja & Ehsani, 2010; Mann, Schumann, & Obreza, 2010). These have focused mainly on the detection of crop yield, quality traits and resulting management measures, such as optimization of pesticide or fertilizer applications. Likewise, identifying spatial variability in biomass, botanical composition and quality characteristics of grassland through RS could provide the basis for improved farm-scale grassland management, for example, with targeted application of fertilizers to areas of low yield, restricted herbicide application to areas with excessive occurrence of weeds, and oversowing or sward renewal on areas with low clover contribution. The combination of real-time RS information on sward biomass and quality with growth predictions from weather-driven models (e.g., Herrmann, Kelm, Kornher, & Taube, 2005) would allow an improved synchronization of feed offer and demand by animals through targeted movement of stock between paddocks. Such a technique could likewise support the implementation of a precise mowing schedule.

In addition, RS may facilitate the monitoring of large-scale conservation grasslands, which is time-consuming when performed by visual evaluation. There is a particular need to improve detection, mapping and prediction of the spatial spread of invasive species, several of which have become a serious threat to many grasslands and natural communities (Mack et al., 2000; Pyšek & Richardson, 2010). Recent results show the utility of RS for classification of invasive species, such as *Lupinus polyphyllus* in mountain hay meadows (Hensgen, Möckel, & Wachendorf, 2017), *Centaurea solstitialis* (Miao et al., 2006) and *Phragmites australis* (Pengra, Johnston, & Loveland, 2007) in wet grasslands, as well as *Psidium guajava* in grasslands and naturals forests of Ecuador (Walsh et al., 2008). Remotely sensed data may, thus, provide a baseline of invasive species distribution for future monitoring and control efforts. Furthermore, information on the spatial distribution of invasive species can help farmers and land managers develop targeted eradication efforts and long-term conservation plans (He, Rocchini, Neteler, & Nagendra, 2011).

5 | CONCLUSIONS AND OUTLOOK

Grassland systems frequently exhibit small-scale botanical and structural heterogeneity with pronounced spatio-temporal dynamics. Such features pose challenges for sensor applications.

Space-borne sensors allow measurements for large areas, but usually have limitations in spectral and/or spatial resolution. Furthermore, the real revisiting time of existing satellites is probably beyond the scope of what is useful for supporting short-term grassland management decisions and the image quality remains very much influenced by weather conditions. In the light of these problems, and the considerable costs of many available RS systems, at the present time (2017), there are only a few commercial applications of RS for practical grassland farming. However, considering the developments over recent decades in sensor performance, data processing and analysis, and modelling, there is potential for significant advances in RS for grassland research and practice. Improvements in spatial resolution are likely to be the main driver that will greatly promote the application of RS. Further increases in spectral resolution can also be expected, which will increase the accuracy of spectral measurements.

Sensors mounted on UAVs usually provide higher spatial resolution, as their flight height is quite low and can be adapted to the needs of the client. Their carrying capacity already allows for the mounting of hyperspectral scanners or cameras and will increase further in the future, as will possible flight time. Compared to space-borne sensors, their temporal availability is much greater and, thus, the influence of weather conditions can be reduced. The challenge will remain for RS developers and users to identify the most suitable sensor and platform for a given practical application. Development of systems with complementary sensors is a very promising research area, which will help to overcome the limitations of single sensors and provide better information about grassland composition, yield and quality.

From an agronomic point of view, the central outcome of RS and data analysis are thematic maps of farm fields which represent the relevant grassland features and constitute the basis for various farm management decisions. These include measures at the (i) strategic level, where long-term decisions are made based on aggregated data over time regarding future scenarios created from downscaled climate scenarios (e.g., farm infrastructure planning); (ii) tactical level, where medium-term decisions are made (e.g., evaluation of clover dry-matter contribution in pastures and choice of crop species for oversowing); and (iii) operational level, where farmers make day-to-day decisions based on spatially explicit real-time data on yield and quality of pastures (e.g., planning of ration, pasture rotation and fertilizer application). Eventually, the overarching goal will be to provide cheap, appropriate and timely information to farmers to support decision-making.

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