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Satellite remote sensing of grasslands: from observation to management–a review

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Abstract

Aims

Grasslands are the world's most extensive terrestrial ecosystem, and are a major feed source for livestock. Meeting increasing demand for meat and other dairy products in a sustainable manner is a big challenge. At a field scale, GPS and ground based sensor technologies provide promising tools for grassland and herd management with high precision. With the growth in availability of spaceborne remote sensing data it is therefore important to revisit the relevant methods and applications that can exploit this imagery. In this article we have reviewed the (1) current status of grassland monitoring/observation methods and applications based on satellite remote sensing data, (2) the technological and methodological developments to retrieve different grassland biophysical parameters and management characteristics (i.e., degradation, grazing intensity), and (3) identified the key remaining challenges and some new upcoming trends for future development.

Important Findings

The retrieval of grassland biophysical parameters have evolved in recent years from classical regression analysis to more complex, efficient and robust modelling approaches, driven by satellite data, and are likely to continue to be the most robust method for deriving

grassland information, however these require more high quality calibration and validation data.We found that the hypertemporal satellite data are widely used for time series generation, and particularly to overcome cloud contamination issues, but the current low spatial resolution of these instruments precludes their use for field-scale application in many countries. This trend may change with the current rise in launch of satellite constellations, such as RapidEye, Sentinel-2 and even the microsatellites such as those operated by Skybox Imaging. Microwave imagery has not been widely used for grassland applications, and a better understanding of the backscatter behaviour from different phenological stages is needed for more reliable products in cloudy regions. The development of hyperspectral satellite instrumentation and analytical methods will help for more detailed discrimination of habitat types, and the development of tools for greater end-user operation.

Keywords:remote sensing; agricultural grassland; grassland biomass; pasture management; grazing intensity

BACKGROUND

Global grasslands

Grasslands are one of the most prevalent and widespread land cover vegetation types, covering 31.5% of the global landmass (Latham et al., 2014). After forests, grasslands are the largest terrestrial carbon sink (Anderson, 1991; Derner and Schuman, 2007) and, as such, they play a vital role in regulating the global carbon cycle(Franzluebbers, 2010; Scurlock and Hall, 1998), as well as supporting plant and animal biodiversity(Bergman et al., 2008; Pokluda et al., 2012; Punjabi et al., 2013; van Swaay, 2002). From an agricultural perspective, grasslands provide the cheapest feed source for the livestock industry, however they contribute both directly and indirectly to climate change through the emission of greenhouse gases (FAO, 2014). As a result, a restriction on a maximum level of grassland intensification (animal stocking) is required in order to minimize the environmental risks

(Soussana and Lemaire, 2014). During the period of 1994to2012,global permanent pasture cover declined by approximately 1% from 3395x10^6ha to 3359 x10^6ha (FAOSTAT, 2014), as a result of urbanization, overgrazing (Piñeiro et al., 2006b; Han et al., 2008), industrial development (Wang et al., 2008), intensive management practices and climate change (Thorvaldsson et al., 2004). Grassland degradation results in increased carbon emissions, has serious repercussions for society (Cardinale et al., 2012), and leads to more complex interactions between grassland ecosystems, management practices and climate change. These human activities, coupled with unfavorable environmental conditions, are major causes of changes in the productivity of grasslands (Xu et al., 2008).

Definition and distribution of managed grasslands

Three distinct categories of managed grasslands are recognised:

Human–generated pastures/meadows/grasslands or improved grasslands: These grasslands are typically created by the conversion of natural landscapes (e.g.forests) into pastures or grassland paddocks (Foley et al., 2005; Hill, 2004).These grasslands areintensively managed in order to maximize production (dairying, meat, wool), for example through regular application of fertilizer, intensive grazing, cutting of silage for winter–feeding and reseeding every few years. Improved grasslands arewidely found in parts ofNorthern Europe, New Zealand and Australia.

Highly managed natural grasslands: In this category natural grasslands are modified and managed to support intensive grazing for thelivestock industry e.g. the semi–improved natural grasslands of eastern Australia, and fescue prairie of Alberta, Canada (Breymeyer, 1990; Hill, 2004).

Rangelands: Based on their species composition, rangelands are different from pastures due to the presence of native herbaceous/shrubby vegetation which are a feed source for

both domestic and wild herbivores e.g. tallgrass prairies (e.g.North American Great Plains), steppes, desert shrublands, shrub woodlands and savanas. Management of rangelands is solely through controlling the number of grazing units and length of the grazing season.

Figure 1 gives an overview of grasslands as a proportion of land cover, with the major managed pastures, grasslands and rangelands areas (Hill, 2004) of the world highlighted.

Grassland monitoring and feasibility of remote sensing technologies

Grassland monitoring, either through in-situ field observation or remote sensing, requires data on the current status of the grass and of the potential offered by the immediate environment, such as soil, weather and human activities. The current status of the grass includes aspects such as sward height, biomass,quality, phenological stage, productivity level, species composition and change in each of these since a previous recording stage (earlier in the same season or in a previous season). In situ methods, from visual analysis to techniques such as a rising plate meter, to cutting and laboratory analysis, can be extremely informative at a local scale, but they are labour intensive and not feasible for large-scale coverage. Remote sensingand modelling approachesallow for large scale monitoring, quantification and prediction(Gao, 2006) of different phenomena (e.g. land use and land cover, biodiversity, impacts of climate change) occurring on the surface of the Earth at varying spatial and temporal resolutions(Nordberg and Evertson, 2003).The integration of multispectral and multi-temporal remote sensing data with local knowledge and simulation models has been successfully demonstrated as a valuable approach to identifying and monitoring a wide variety of agriculturally related characteristics (Yiran et al., 2012; Oliver et al., 2010). In the context of global food security and to avoid food shortages, estimated yield production prior to harvest is needed for planners and decision makers, and remote

sensing platforms are increasingly recognized as essential tools for this task(Boschetti et al., 2007). An early and accurate indication of a decrease in fodder production is especially important for agriculture-dependent developing economies, however, to date, little work has been undertaken on grass–based food security. Recently Svoray et al. (2013) has published a detailed review on remote sensing of rangelands, so this review focused on managed grasslands and pastures for their greater relevance to agriculture, livestock and the concept of precision farming from space (precision agriculture).

Objectives and scope of the review

This article will review the application of satellite remote sensing for grassland and its transition from grassland mapping to grassland/pasturemonitoring and management. The aims of this review are to examine the extent of satellite remote sensing applications in the field of grasslands and pastures, and to identify the contemporary trends and future potential of these data and methods. The main objectives of this paper are:

- to provide an overview of satellite remote sensing (optical andmicrowave) technological and methodological developmentsto retrieve different grassland biophysical parameters and management characteristics
- to identify trends and gaps in the work done to date resulting in recommendations for future research and operational systems.

APPROACHES TO GRASSLAND MONITORING

Grassland monitoring approaches are broadly categorized into two groups: (i) ground-based, and (ii) remote sensing methods. The term “grassland management” in the context of this research includes weed control, removing dead plants, mowing, clipping, assessment of

biomass and growth rate, extent, grazing length, and utilization of grassland (incorporating elements of herd management)(Hybu Cig Cymru, 2008).

Ground based measurements for validation of remotely sensed data

Ground-based grass monitoring techniques heavily depend on an infrastructure which includes in situ data collection stations, measurement devices and frequent field surveys (del Pozo et al., 2006). Current methods used for the retrieval of grassland biophysical parameters and other management related information include:

Visual: visual assessment by human eye (expert or farmer), this method is spatially sparse with limited performance for different management strategies (Newnham, 2010).

Cut and dry (clipping): grass harvested from the paddock is dried and weighed to get the dry matter (DM) yield, as well as a laboratory assessment of grass quality and nutrient status(Xie et al., 2009).

Rising plate meter (RPM): both mechanical and electronic plate meters work on the principle of a plate rising up and down the shaft taking measurements of grass height (Castle, 1976; Hakl et al., 2012; Hejcman et al., 2014). This method is most commonly used for accurate biomass and grass height estimation at a point but is very time intensive.

Field spectrometry:reflectance spectra are collected using a spectrometer held at waistheight and are calibrated against in situ samples, with species discriminatedusing local field data or spectral libraries. Based on the reflectance at red and near infrared wavelengths, vegetation indices (VIs) are calculated, from which biophysical parameters such as above ground biomass and leaf area index can be retrieved (Flynn et al., 2008; Psomas et al., 2011a). Flynn et al. (2008) used a ground-based sensor to calculate the Normalized Difference Vegetation Index (NDVI) in order to investigate the within-field

variability in biomass and assess the potential for the application of NDVI for pasture management activities. They found that NDVI showed a good correlation with biomass ($r^2 = 0.68$) and with the results from the rising plate meter ($r^2 = 0.54$), however as noted by Todd et al. (1998), possible relationships between such indices and the vegetation biomass are influenced by the ground-based sampling methods, for example biomass can be underestimated due to the presence of non–photosynthetically active plant material.

Table 1 gives the summary comparison of different ground-based methods.

While these ground–based methods are very useful for grassland monitoring on a local scale, and for providing values for model development and calibration of ex situ data, they are subjective, time consuming and are only feasible (or applicable) for small scale assessment (Xu et al., 2008).

For remote sensing studies, high quality ground truth data are of great importance for cross validation and algorithm training. All these ground-based methods are equally applicable for this purpose, and data collected using these methods have proven very useful. For example forest inventory, crop yield and grassland (Xu et al., 2008)data collected in past is currently being used by the remote sensing scientists for forest change detection and development of yield estimation models.

Remote sensing methods

As highlighted in the field spectrometry discussion of section 2.1, measurement of the reflectance at visible and infrared wavelengths can enable discrimination of different grassland species and status.These principles are equally applicable forlocal scale mapping and monitoringfrom optical sensors mounted on eddy covariance towers, unmanned aerial vehicles,aircraft and spaceborne platforms. It is these spaceborne platforms that can collect

data at spatial scales from 25cm to 1km, for regional, national and global studies, that are the focus of this review. The last 20-30 years have seen many technological developments that enable economically cost effective, statistically reliable and consistent, and operationally robust tools for remote monitoring of grassland sites and acquisition of data on their behavior.

Optical remote sensing

Discrimination of different terrestrial ecosystem types andmeasurement of their productivity primarily relies on vegetation indices (VI) that combine reflectance values at two or more wavelengths, selected to accentuate particular features of the spectral signature, such as greenness, water content or light use efficiency(Song et al., 2013). Given the similar composition, and therefore spectral signature, of many grassland sites, data at multiple wavelengths allows more robust characterization of grassland speciesand their biophysical parameters. This has been facilitated by the trend in recent years for satellite sensors to record a higher number of carefully selected wavelengths, e.g. the yellow band of Worldview-3is designed to detect ripening or dying plants. The red–edge, where there is a rapid increase in reflectance from the red to NIR reflectance (around 680-730nm), has been shown to have a strong correlation with the grass chlorophyll content of the canopy ($r = 0.93$) and the leaves ($r = 0.86$) (Pinar and Curran, 1996). Inclusion of measurements made in a red-edge channel are thus a reliable indicator of foliar chlorophyll content and vegetation stress (Dawson and Curran, 1998), and are also useful for assessment of plant chlorophyll concentration, leaf area index and therefore nutritional status (Filella and Penuelas, 1994). With the launch of RapidEye, the first high-resolution multispectral satellite system that operationally provides a red edge channel, Schuster et al. (2012) reported a higher classification accuracy for managed grassland typesthan could be achieved without inclusion of measurements at this

wavelength.Hyperspectral remote sensing data, which record a larger number of wavelength bands, therefore offer the opportunity of defining new vegetation indices that can be tailored to a particular species and/or parameter application(Clevers et al., 2007).

Although increased spectral resolution offers significant benefits to resolving species composition at a single point in time, it is recognised that a time series of imagery acquired through the growing season provides maximum information on yields and management. Phenological stages of grasslands can progress rapidly during the growing season as a function of factors including weather, germination, management strategies, grazing pressure/intensity, hydrological processes and nutrient input.Huang and Geiger (2008)demonstrated that inclusion of grass phenological stages increased the accuracy of mapping grass cover, andButterfield and Malmström (2009)showed that understanding of grassland dynamics could be improved through looking at biomass-NDVI relationships at different phenological stages. An increased temporal frequency of image acquisition is advantageous in countries with cloud-dominated climates where multiple overpasses fail to generate an image of the ground.O'Connor et al. (2012)highlighted the benefits offered by a dense time series of 10-day compositesfor mapping spatial variability in vegetation seasonality in Ireland, with landcover classes separated on the basis of their start of season greening. The benefits of timely imagery are recognised for yield estimation from crops (Morel et al., 2014),and with an increased number of spaceborne sensors available in a constellation, there is an increased potential to acquire more frequent, cloud-free imagery coincident with key stages in the grass growth season.

There is typically an inverse relationship between the frequency of image acquisition and the swath width of the sensor and its spatial resolution, which results in the sensors that acquire daily images doing so at resolutions of 300-1000m. While this may be sufficient for large rangeland areas, it is often too coarse for imaging intensively managed grasslands, and where

the pasture paddock size is smaller than the sensor resolution cell, inconsistency and discrepancies with in situ data validation arise in averaging and aggregation during up and down scaling for multi sensor data integration (Hill, 2004). Due to the small size of many managed agricultural grassland paddocks, access to high spatial resolution imagery is essential in determining inter- and intra-field variations. Figure 2shows the false color composite of a managed grassland areawhere small-scale differences in growth are more evident in the 2.4m Quickbird image than the 6.5m RapidEye image, and almost impossible to detect in the 30m Landsat–8 scene.

A number of high and very high-resolution sensors have been launched in the last 10 years which enable such intra-field variations to be detected, and when multiple identical instruments are in a constellation a time series of cloud-free imagery can be maintained. However thescale of imaging remains a very complex and dynamic topic in the context of remote sensing, with Wu and Li (2009) and Quattrochi and Goodchild (1997) providing more detailed discussion on this topic.

Microwave remote sensing

The use of optical instruments for vegetation mappingis common practice, with a good understanding of the relationship between reflectance and biophysical information, however it is limited to periods when the target is illuminated by the sun under cloud-free conditions. In recent years there has been a growing interest in the potential offered by microwave spaceborne instruments which measure the strength of the backscattered signal from the surface under almost all weather and light conditions, allowing frequent repeat measurements throughout the growing season. While the number of wavelengths utilized by active microwave instruments is relatively limited, synthetic aperture radar (SAR) instruments offer a number of different acquisition modes, with different polarizations, incidence angles and

orbital directions (ascending/descending). The backscatter signal from vegetated surfaces is a function of the soil surface, the radar system, and the biophysical parameters of the scatterers in the vegetation that can influence the depth to which the radar wave penetrates. Different theoretical approaches have been developed to interpret the backscatter signal, for example the water cloud model in which the total backscatter signal comprises components from the soil, vegetation and attenuation(Attema and Ulaby, 1978).A number of SAR instruments have been launched during the 21st century that have allowed advancement of microwave remote sensing of vegetation phenology, for example TerraSAR-X, with a very high resolution (up to 1m) X-band sensor, and the COSMO–SkyMed constellation of four X-band platforms which were used by Hajj et al. (2014) to investigate the sensitivity of radar signals to soil moisture and vegetation within irrigated grassland plots. The Japanese ALOS and ALOS-2 L-band instruments, and European Space Agency ASAR and Sentinel–1 C–band platforms have a lower spatial resolution but the longer wavelength can be more sensitive to vegetation volume, as shown by Barrett et al. (2014) in discriminating between grassland types in Ireland. A number of studies have been undertaken to compare the sensitivity of the different wavelengths to vegetation conditions (e.g.Gao et al., 2013; Inoue et al., 2002), with Metz et al. (2012) demonstrating how the most accurate discrimination of European Natura 2000 protected sites and high nature value habitats could be achieved with combined use of a TerraSAR–X and Radarsat–2 time series.In addition to using different wavelengths for different applications, the different polarimetric acquisition capabilities can be exploited e.g. Voormansik et al. (2013) used a TerraSAR–X dual polarimetric SAR time series to detect grassland cutting practices, and Buckley and Smith (2010) used a combination of multi angle Radarsat–2 quad-polarisation images, demonstrating improved grassland classification results when compared to the individual incidence angles.

However, a number of limitations have constrained the work done in the microwave domain, predominantly the difficulty of distinguishing the signal response associated with vegetation cover from moisture and acquisition conditions. The inherent speckle of SAR imagery also requires processing that reduces the spatial resolution, and thus can lose some of the detail that may be present at the scale at which the image is acquired. To overcome these limitations and derive conclusive results has typically required intensive ground-based measurements (Moran et al., 1997).

Several studies have been carried out to compare the outputs from optical and microwave instruments. Smith and Buckley (2011) did a comparative analysis of Radarsat–2 and Landsat–5 TM for the classification of cultivated crops, summer fallow, improved and native grassland. Even though the classification accuracy for Radarsat–2 (kappa: 0.65) was less than that for Landsat–5 TM (kappa: 0.81), due to the backscattering similarities between native and improved grasslands, it was able to successfully discriminate between the cultivated crops and grasslands. By contrast, in a recent study Dusseux et al. (2014) reported classification results of fully polarimetric Radarsat–2 (98% accuracy) that outperformed the optical imagery (SPOT–5 and Landsat–5 TM, 81% accuracy).

It is apparent that there have been many developments in the use of remote sensing for vegetation monitoring, mapping and management in recent years, with a number of reviews dedicated to specific aspects of agricultural and ecosystem practices (e.g., Atzberger, 2013; Shoshany et al., 2013).In an early review paper, Tappan (1982) highlighted some topics for future research using remote sensing for grassland applications e.g., biomass estimation, instrument calibration and use of high spatial and temporal resolution satellite platforms. To date however, available reviews on grasslands have focused either on a site-specific approach (e.g. Trotter, 2013), or on just classification and mapping of grasslands (Booth and Tueller, 2003; Svoray et al., 2013; Xie et al., 2008). The following review broadens this focus to

address some of the issues raised by Tappan (1982) on spaceborne remote sensing within grassland environments, and the transition from grassland classification/mapping to grassland management.

REMOTE SENSING OF MANAGED GRASSLANDS AND PASTURES

Classification

The motivation for grassland mapping includes distinguishing different grassland ecologies that may reflect management practices, grassland degradation and estimation of grassland productivity trends over time. Data (and/or derived products) from Landsat TM/MSS, SPOT, AVHRR, MODIS and RapidEye sensors amongst others have been most commonly used for the purpose of land cover classification and land cover change mapping, including grass–based habitats such as rangelands, pastures and meadows. Many of the studies have been undertaken using optical rather than SAR sensors, which reflects their longer history of operation, the importance of the red and NIR bands for vegetation discrimination, and the availability of data at a range of resolutions, including sub–meter for field scale work and 1km for global mapping.

Discriminating between grassland types is usually achieved using either statistical, object-oriented or machine learning classification approaches. The maximum likelihood classification approach was widely used until the 1990s, with typical overall classification accuracies in the range 70–90%.For exampleToivonen and Luoto (2003) mapped grasslands in Finland from Landsat data with an overall accuracy of 89%, although the classification accuracy was as low as 63% for the semi–natural grassland class. Similarly, Jadhav et al. (1993) achieved an overall accuracy for grassland mapping in India of 82%, and Baldi et al. (2006) distinguished South American grasslands with accuracies of 90–95%. While some studies using these statistical classifiers performed very well, in general the complexity of

grasslands and the spectral similarity of different grassland types limits the value of these approaches. Furthermore, these statistical approaches have a limited capability to determine boundaries between different natural grassland ecologies. Brenner et al. (2012) compared object and pixel classification approaches for classifying Buffel grass in Mexico from satellite imagery, and found that determining objects on the basis of their contiguity allowed for more accurate results. Decision trees permit data from different sources to be included to aid distinguishing between grassland classes and also to preclude some misclassification opportunities, as Dubinin et al. (2010) showed with a multi–sensor approach to assess annual burned areas in the grasslands of southern Russia, and Wang et al. (2010) discriminated between warm and cold season grasslands in the USA from ASTER data with an overall accuracy of 80%. Peña-Barragán et al. (2011) developed a hybrid classification strategy, combining object based image analysis with a decision tree (DT) including information on textural features and phenology, to classify ASTER imagery of California. While some of the 13 classes were very reliably classified with accuracies of 95%, others remained problematic with only a 50% chance of being correctly labelled. A hybrid classification approach was also adopted by Masocha and Skidmore (2011) to map an invasive species in part of southern Zimbabwe. Artificial Neural Network (ANN) and Support Vector Machine (SVM) approaches gave accuracies of 71% and 64% respectively, but after incorporating the information from a GIS expert system the accuracies increased to 83% and 76% respectively. In addition to mapping different grassland ecologies or species, classification approaches have also been used to assess grassland use intensity and to monitor changes over time. Tovar et al. (2013) used object-based classification of Landsat imagery of Peru to analyse trends in land use and land cover from 1987–2007, with an overall accuracy of 80.3%, showing an annual decrease in the spatial extent of the Jalca grasslands of 1.5%.

Many grassland studies have been conducted at a local scale using high spatial resolution imagery, but the same methods can be applied to a national or regional scale using coarser spaceborne imagery (e.g. MODIS).In a recent study, Nitze et al. (2015) established the value and consistency of a machine learning algorithm for the classification of improved and semi-improved grasslands in Irelandfrom a 9 year MODIS time series of NDVI and enhanced vegetation index(EVI) vegetation indices. In order to optimize the data acquisition period, the importance of different features was considered in this study, with the authors concluding that to achieve an accuracy of more than 90%, only 6-10 images are required per year.

In general, optical sensors have been preferred to SAR sensors for classification of grasslands, exploiting the multispectral information acquired at the shorter wavelengths. For example, Price et al. (2002) conducted a comprehensive study to compare the use of Landsat TM and ERS-2 C–band SAR data in order to discriminate different grassland types under different treatments in eastern Kansas. In this study, Landsat TM and ERS-2 were used to discriminate between the cold and warm season grass species, with discriminant analysis showing that both types can be distinguished, with an accuracy of 90.1% using Landsat TM data, but only 73.2%using ERS-2 SAR data. Three management strategies were also classified, with an accuracy of 70.4% (Landsat TM) and 39.4% (ERS-2 SAR). The last step in this study was the combined use of Landsat TM and ERS-2 SAR data, and it was found that the SAR contribution to the discrimination of the grassland types was statistically significant. In another study,Smith and Buckley (2011) used Radarsat-2 C–band polarimetric SAR data in order to discriminate improved grasslands, native grasslands and agriculture crops, and again Radarsat-2 classification results were less accurate than the Landsat TM (Kappa coefficient: Radarsat-2 = 0.65, Landsat TM = 0.81). Interestingly however, the latest generation of high resolution SAR sensors, such as TerraSAR-Xand ALOS–2, show greater potentialfor information retrieval from grassland pastures at smaller scales, allowing changes

in surface roughness and moisture, typical of different grassland regimes, to be better detected. Wang et al. (2013) compared satellite imagery from three different SAR (X, C and L-band) sensors and showed that X-band SAR data has the highest correlation with the vegetation indices. Barrett et al. (2014)highlighted the value of machine learning classifiers for discriminating different grassland types using multi–sensor C and L–band SAR data.

In summary, classification of grassland types and formations using satellite remote sensing data has been successfully applied using different classifiers and sensors in different regions of the world.Table 2highlights a number of studies that have been done since 2000 using spaceborne remote sensing data for mapping different aspects of grasslands around the world. The majority of these studies are from optical sensors, emphasising their suitability for vegetation mapping and the availability of high resolution optical data (Franke et al., 2012), as well as a good understanding of the relationships between the data and biophysical plant parameters.

Biomass estimation

Gao (2006) addressed the difficulties and importance of remote sensing based quantification of grassland properties. For example, *(i)*the date of image acquisition and ground truth collection must be the same or very close to each other, *(ii)*samples must be selected randomly, *(iii)*a sufficient number of samples(at least 30) is needed, *(iv)*the use of GPS during ground truth collection so that in situ measurements and corresponding pixels correctly overlie each other, and *(v)* if the grassland is highly dynamic then high temporal resolution satellite time series should be used instead of a single image. Methods for remote sensing of grass yield estimation can be broadly grouped into three strategies: development of yield estimation regression models based on different satellite driven VIs, use of different machine

learning algorithms (e.g. ANN, SVM), and combined use of remote sensing driven vegetation parameters and biophysical simulation models (e.g. WOFOST, Lingra).

Vegetation index based regression models

Remote sensing of biomass estimation has been undertaken for many years, and numerous studies show a good correlation between in situ measurements and VIs derived from satellite data(e.g. Wylie et al., 1991; Anderson et al., 1993). Boschetti et al. (2007) assessed pasture production in an alpine region using field spectrometry and Landsat-7 imagery, with integration of these data, via regression analysis, supporting assessment of pasture production. Ullah et al. (2012) used MERIS data and analysed different VIs for the estimation of grassland biomass in the northern Netherlands, where NBDI (normalized band depth index (Mutanga and Skidmore, 2004)) produced better results than the more conventional VIs (NDVI, soil—adjusted vegetation index SAVI, and Transformed SAVI (TSAVI)). Xu et al. (2008)tested three different regression modelsusing MODIS derived NDVI and ground measurements of grass yield for the estimation of grass production in China, where more than 8000 samples were collected from 17 grassland dominant provinces and regions, with the best correlation shown for an exponential relationship (linear$r^2 = 0.671$, power$r^2 = 0.794$ and exponential$r^2 = 0.805$). In the north-eastern province of China, Zha et al. (2003) found a high correlation($r^2 = 0.74$) between NDVI, derived from Landsat TM and field spectrometer measurements, and the percentage of grass cover. By contrast, An et al. (2013) used biweekly AVHRR NDVI values to predict above ground net primary production (ANPP) in a tall grass prairie system, but their model, validated by in situ measurements, was less able to predict year-to-year ANPP variations ($r^2 = 0.54$), with the coarse resolution (1 km), and thus the influence of mixed pixels, a possible explanation for this low value of coefficient of determination. As plant phenology is highly influenced by inter-annual changes

in temperature and precipitation, Lee et al. (2002) investigated the influence of climatic variation on plant phenology in Inner Mongolia by analysing a 9-year (1982-1990) AVHRR NDVI time series and monthly mean temperature and precipitation. However they reported little or no change in phenological response during this period, which could again be attributed to the low spatial resolution of the imagery.

A major challenge in the use of VIs to assess vegetation parameters is to minimize the influence of external factors and to maximize the sensitivity of the relationship between VIs and biophysical parameters. Many authors have tried to find the most suitable subset of VIs (e.g. those for best estimation of biomass for a particular type of vegetation), with some advocating a move away from the index-based approach. Even though many researchers have established significant relationships between VIs and vegetation parameters in the context of a single study, many such models are site or season specific, and the successful transferability from one site to another is variable. Based on the combined use of field spectroradiometer data and satellite driven indices, Boschetti et al. (2007) concluded that log-transformed regression analysis between soil-adjusted VIs and fresh biomass show higher correlation than aratio vegetation index or NDVI. Likewise,Ullah et al. (2012) showed that band depth analysis outperformed the use of traditional VIs when they modelled vegetation parameters and spectral values by simple linear regression and stepwise multiple linear regression (MLR), and continuum removed spectra—normalized reflectance spectra used to compare individual absorption features—were used to calculate band depth parameters.

Table 3 presents a summary of several studies conducted since 1990 on grass yield estimation derived using vegetation index based approaches, with many of the better results achieved at a local to regional scale.

Machine learning models

ArtificialNeural Network (ANN) models belong to a powerful class of empirical modelling with the capability of computing, predicting and classifying data, and are more versatile than linear regression models. The use of machine learning algorithms for estimating crop yields e.g. corn (Panda et al., 2010; Serele et al., 2000) and rice (Ji et al., 2007) has been widely reported, however only a limited number of studies have been described for their application to estimation of grassland above-ground biomass (dry matter)(Ali et al., 2015, 2014). Xie et al. (2009) compared the performance of ANN and MLR for above-ground grassland biomass in the Xilingol River Basin, Inner Mongolia. Topographic, vegetation index and spectral information from Landsat ETM+ were used as input data, with ANN generating a better yield estimation than the MLR ($r^2 = 0.817$, $RMSE = 42.36\%$ compared to $r^2 = 0.591$, $RMSE = 53.20\%$). In another study,Yang et al. (2012) used a back propagation ANN algorithm for grassland yield estimation based on five VIs derived from MODIS satellite data, with NDVI and SAVI showing the best fit with the in situ sample biomass. Once again, the ANN models were more accurate ($R^2 = 0.56–0.71$) than the statistical models ($R^2 = 0.54–0.68$).

Mountrakis et al. (2011) comprehensively reviewed the application of SVM in satellite remote sensingapplications but itsuse for biomass estimation is not discussed. A limited number ofstudies have applied SVM to biomass assessment from satellite imagery (e.g. Jachowski et al. (2013), for mangrove ecosystems), but there is no reference to it being used for grassland biomass. Thepotential of SVM forgrassland biomass estimation was established by Clevers et al. (2007) with a band shaving algorithm to identify highly correlated bands inairborne hyperspectral data and thus develop the most predictive band ratio. With the development of new hyperspectral satellite instruments, the potential for powerful species and site specific indices will be enhanced.

Simulation models

For indirect vegetation biomass estimation, simulation modelling techniques are used, whereby remote sensing data are used as an input variable or substitute for vegetation parameters. In order to better understand the growth mechanism and spatial variability of grasslands, meteorological data driven models have been used to simulate and predict the grassgrowth rates (Barrett et al., 2005; Bouman et al., 1996; Moore et al., 1997; Woodward, 2001). The precision of these models heavily depends on their ability to incorporate multisource data over different spatial scales for yield estimation(Hansen and Jones, 2000). Some authors (Brilli et al., 2013; Maselli et al., 2013, 2006)have explored the potential application of the parametric model C-Fix, a Monteith type parametric model driven by temperature, radiation and fraction of Absorbed Photosynthetically Active Radiation (fAPAR), for the estimation of gross primary productivity of grasslands, olive groves and forests in Italy. Parameters derived from satellite data and ground measurements are combined in order to simulate the total production. Maselli et al. (2013) compared the efficiency of C-Fix and the BIOME-BGC biogeochemical model for grassland productivity, demonstrating that the parametric model performed better, with a root mean square error of 49.7 gDM $m^{-2}y^{-1}$ compared to 85.4 gDM $m^{-2}y^{-1}$for the BIOME-BGC model.

In summary, regression models based on VIs have predominantly been used for grass yield estimation. Machine learning algorithms are proving to be powerful tools for grassland classification, but still need to be further developed for grass yield estimation (Mountrakis et al., 2011).The fusion of multi-source data into biophysical simulation models also requires further research in order to better exploit their suitability and transferability.

Grazing management

Grazing impacts

Degradation in grasslands and rangelands is a very complex and dynamic phenomenon caused by natural and anthropogenic activities (Paudel and Andersen, 2010) which can be assessed at a small scale by an expert opinion or visual evaluation, however, for national or global scale evaluationthe use of remote sensing technology is a more feasible approach.Tueller (1989) first described the application of aerial photography and satellite imageryto support management of rangeland resources, but the quality and quantity of satellite imagery available at the time proved a limiting factor. Tueller did however predict that within 20 years the majority of required management information would be available from satellite imagery, a prediction realised by Munyati and Makgale (2009) who used a time series of Landsat TM imagery to map and quantify degraded rangeland in South African communal grazing lands.Pickup et al. (1994) first used satellite data for the assessment of land degradation by combining image derived vegetation cover index values and spatial models of grazing density determined as a function of distance from a watering point.Trends in rangeland degradation (Pickup et al., 1998) were also identified from imagery,with a vegetation cover model built from multi-temporal remote sensing data in order to distinguish between natural and human impacts on degradation. With a longer time series of Landsat data to derive locations of persistent ground cover, Bastin et al. (2012) demonstrated that it is also possible to discriminate between natural and human induced grazing effects on ground cover in Queensland. Other studies have also exploitedmulti-temporal datasets for degradation assessment (Paudel and Andersen, 2010),mapping and quantification of degraded areas at different scales (Alves Aguiar et al., 2010), and in combination with GIS technologiesto investigate changes in grassland cover(Zheng et al., 2011).

Remote sensing technology is not only useful for the identification of degraded areas, but also for mapping, monitoring and quantifying restoration of such degraded land after the implementation of corrective measures. A ban on grazing was imposed in Ningxia province of China in 2003 to decrease degradation, and in a recent studyLi et al. (2013) used Landsat imagesto map the positive outcomes of this ban, with 59.41% restoration reported between 1993 and 2011. Huang et al. (2013) also successfully demonstrated how such techniques could be used to effectively evaluate trends in degradation after the implementation of restoration programs using AVHRR (1982–2003) and MODIS (2000–2008) remote sensing images.

In summary, remotely sensed imagery has been successfully used for detecting degradation and recovery of grassland areas. More research is needed to fully explore the data from newly launched high resolution SAR sensors because in degraded areas grass cover is sparse with open soil, and more work is required in order to better understand the backscatter response from such sites.

Assessment of grazing capacity and intensity

Grazing management strategies are directly linked to factors including grazing intensity, length of grazing period, grazing regimes, stocking rate and elevation(Bradley and O'Sullivan, 2011; Vermeire et al., 2008; Volesky et al., 2004), and vary from area to area in order to meet livestock grazing management goals. Grazing intensity has the most influence on grassland productivity, and overgrazing can cause grassland degradation (Boddey et al., 2004) with some studies showing that light to moderate grazing intensity practices can enhance grassland productivity under certain environmental conditions (Luo et al., 2012). Remote sensing approaches can be used to monitor livestock grazing (Feng and Zhao, 2011) at light to moderate intensity(Xiaohui Yang et al., 2012; Yang and Guo, 2011).Kawamura et

al. (2005b) used NDVI derived from remote sensingdata for the quantification($R^2 = 0.77 - 0.83$) of grazing distribution in Inner Mongolian grasslands. In another study, Numata et al. (2007) used Landsat TM data in order to analyse the impact of grazing intensity on a pasture's biophysical features, with remotely sensed non–photosynthetic vegetation showing the highest correlation with grazing intensity ($r^2 = 0.70$) compared to the other measured biophysical features e.g.above ground biomass, canopy height and water content.

Consistent and frequent monitoring ofthe effects of grazingintensity is crucial in arid, semi–arid and commercial grazing pasture areas, as grazing intensity influences the grassland ecosystem(Röder et al., 2008) both in a positive and a negative manner. An example of apositive influence is given by Cohen et al. (2013) for a high latitude, intensively grazed area, where late snow melt means the surface is protected from heating for longer, and, as snow has a high albedo, it can easily be analysed from image data. Studies show that at high latitudes where the vegetation is tall, dense snow melts earlier (Loranty et al., 2011; Marsh et al., 2010) compared to the short vegetation. In response to Hein's (2006), findings Retzer (2006) reported that high resilience after drought may be due to the precipitation dynamics not because of high intensity grazing as suggested by Hein (2006).

Careful consideration of sampling scale is very important in remote sensing studies, and needs to be determined according to the application. Yang et al. (2011)tested the significance of measured biophysical parameters (canopy cover, height and LAI) to find the difference between grazed and ungrazed sites,where for canopy height, and ratio of photosynthetically active and non-active vegetation cover,the difference was significant. Among the various spectral vegetation indices,red and NIR based measures showed the most significant correlation with canopy height. This analysis was based on single dates and suggests the use of multitemporal remote sensingdata for evaluating pre and post-grazing vegetation

conditions. A combination of remote sensingand GIS models can be used for the evaluation and classification of study sites based on their suitabilityfor grazing (Bozkurt et al., 2011).

In grassland management and the livestock business, grazing capacity and intensity are the key factors that need to be monitored consistently in order to optimize the feeding resources. Information extracted from satellite remote sensing has been shown to be useful forestimatinggrazing capacity—the maximum number of animals that can be sustained in a given area of pasture in a year—and intensity, which is required for nutritional planning of livestock. For the assessment of short–term grazing capacity at paddock level, Phillips et al. (2009) developed a model based on remote sensing and ground-based data on cattle nutrition. They observed the underestimation of grazing capacity by the model and suggest additional testing of the model and at multiple sites. Along with additional testing at multiple sites, use of very high resolution data (e.g.GeoEye–2: 1.35m, WorldView–3: 1.24m) might be valuable to correct this anomaly. Wu et al. (1996) proposed a physical model for simulating productivity in grazing ecosystems, withBénié et al. (2005)developing the model further to include remote sensing and socio-economic parameters in order to simulate the available biomass or carrying capacitywith an accuracy of 80%. The use of remote sensing data becomes a challenge in applications where the underlying target area is composed of sparse vegetation and highly reflective soil. In order to overcome this problem,Edwards et al. (1999) proposed a geometric optical model based on low resolution satellite imagery whose output is a series of change maps that can be used to estimate the final vegetation cover. A very high correlation between observed and estimated vegetation cover was reported ($r^2 = 0.837$), but even though the approach was quite useful no further applications of this approach can be found. Similarly, no reference to SAR data for assessment of grazing capacity and intensity is evident in the literature.

In summary, identification of grazing capacity and intensity is required in order to avoid overgrazing and degradation, but there is a very fine distinction between normal grazing and overgrazing, and in order to better understand this transition the use of very high resolution optical data, SAR data, and a combination of both needs further investigation.

Pasture quality and status

Grazing capacity depends not only on the grassland spatial extent but also on the quality of grass, which is directly linked to livestock feeding. While the potential of remote sensing based classification and mapping of grassland quality has been long recognized (Giraed et al., 1990), only a limited number of studies have been done on grassland quality assessment using this approach. The range of data used varies between coarse (Kawamura et al., 2005b; Si et al., 2012), medium (Kawamura et al., 2005b) and high (Guo et al., 2005; Si et al., 2012) spatial resolution. Studies show that the leaf area index (LAI) is considered as more appropriate for the assessment of grassland health, biomass and plant water content than the satellite derived NDVI (Guo et al., 2005). In a recent study, Falldorf et al. (2014) developed a remote sensing based tool called the Lichen Volume Estimator (LVE) to assess winter pasture quality (in terms of volume) by using a 2D Gaussian regression model based on a Normalized Difference Lichen Index (NDLI = MIR-NIR/MIR+NIR) and Normalized Difference Moisture Index (NDMI = NIR-MIR/NIR+MIR). The authors concluded that LVE could become an important tool to assist in prediction of winter grazing areas for reindeer and caribou herds at one location, and with further field studies it could become more widely applicable. Multispectral remote sensing data has also been used in combination with in situ data (Zerger et al., 2011) and models such as the radiative transfer model PROSAIL(Quan et al., 2015; Si et al., 2012) for the assessment of vegetation/grassland condition and quality. The inversion(Si et al., 2012) of the PROSAIL model and MERIS reflectance data (single

biome approach) has great potential to estimate the grassland LAI ($R^2 = 0.70$) and canopy chlorophyll content ($R^2 = 0.61$). Hill (2013) simulated ESA Sentinel-2 (high resolution optical sensor) data and showed that VIs based on these bands can be used for the identification of vegetation states in grassland and savannas.

In summary, pasture quality and status are directly related to grassland management. Detailed investigations on the use of hyperspectral remote sensing data are required, and to exploit the large number of bands different VIs at different wavelengths can be calculated in order to retrieve multiple vegetation parameters.

Pasture growth rate assessment

To meet the increasing demand for food, optimisation of agricultural production and effective resource management are critical. Precision agriculture involves real or near real-time data collection about the physical and/or chemical properties of the target vegetation in order to assist decision making through the use of predictive tools and forecasting models. For satellite based precision agriculture, the spatial resolution, satellite revisit frequency and number of spectral bands are the key factors that are related to the acquisition of a dense time series for consistent monitoring at a farm or paddock scale. Much of the work done to date on this subject has been focused on croplands using field spectrometry (Gutiérrez et al., 2008; Prabhakar et al., 2011; Zhang et al., 2003), airborne imagery(Epinat et al., 2001; Erives and Fitzgerald, 2005) and satellite data (De Benedetto et al., 2013; López-Lozano et al., 2010; Nahry et al., 2011; Thenkabail, 2003), and it is only very recently that grassland management and precision farming has been considered. The *"Pastures From Space*[1]*"*project in Australia is one of the most prominent, and has developed a dedicated grassland/pastures tool to deliver near real-time information (e.g. biomass, growth rate) at the farm and paddock level using

[1]http://www.pasturesfromspace.csiro.au

high and medium resolution satellite remote sensing(Donald et al., 2004; Edirisinghe et al., 2011; Henry et al., 2004). The techniques were developed and validated in Western Australia over a five year period, and then transferred and verified in Southern Australia, and the project is providing online (web and also software based) pasture growth rate at weekly regional and paddock scales. Schellberg et al. (2008) wrote a detailed review focusing on precision agriculture of grasslands, in which they discuss the applications of different remote sensingtechniques for the monitoring of physical, chemical and area-based grassland properties for farm related decision-making.

Pasture growth rate is a biophysical property (monitored as kg dry matter/ha per day) which is related to how much grass grows on a daily basis and is an important driving factor for feed budgeting related decisions. Apart from management practices, climatic factors also influence the growth rate of grasses (Thorvaldsson et al., 2004). There is no precipitation component in the C-Fix model (as discussed in section 3.2.3) but the Australian *"Pastures From Space"* model differs by including precipitation as well aslight use efficiency (LUE) models (Hill et al., 2004; Piñeiro et al., 2006a), data integration (Hill et al., 1996; Moore et al., 1999) and classification (Vickery et al., 1997)tools for growth rate prediction (Donald et al., 2010), monitoring and mapping.Multisource (e.g., Landsat, SPOT, MODIS, AVHRR, Hyperion) remote sensing data with different spatial resolutions were used to successfully assess the growth rate at different spatial scales(Donald et al., 2004; Henry et al., 2004).

"Pastures From Space" is an effective tool for near real–time monitoring at farm and paddock level in order to better manage the feed resources for livestock industries, but currently represents the only operational system designed specifically for pastures. Schellberg and Verbruggen (2014) discuss the delay in transferring techniques developed for arable land to grassland,although there is scope for the successful implementation of emerging technologies such as precision agriculture in a variety of environments. After the successful

implementation and validation of the *"Pastures From Space"* project, in2003 Fonterra[2] formed a partnership with CSIRO in order to explore its potential in New Zealand dairy farming and pasture monitoring, and various studies have been done since then (Ausseil et al., 2011; Dymond et al., 2006; Edirisinghe et al., 2012; Mata et al., 2010).

In summary, both airborne and spaceborne remote sensing data are being used to collect real time (or near real time) information on pasture yields and growth rates. Based on satellite remote sensing data, decision support systems can be developed for farm related management decisions.

Transhumance

In mountainous regions there is an annual cycle of livestock migration to the higher elevation pastures in warm seasons and return to lower altitudes for the rest of the year, with a concurrent cycle of high grazing intensity and pressure. Such transhumance, or herd mobility, is one of the key components for sustainable use of these upland resources (Sitters et al., 2009) that are highly sensitive to environmental changes, and for that reason it is essential to monitor their land cover dynamics (Morán-Ordóñez et al., 2011). Satellite imagery has considerable potential to detect and map land use,their corresponding effects on livestock feed resources and feed deficit management strategies (Mekasha et al., 2014). Butt et al. (2011) used a MODIS NDVI time series from 2000–2010 in order to evaluate the gradient of rangeland phenology with respect to the changing latitude and its effects on the direction and timing of livestock movement in the Sudano–Sahelian region in West Africa. A double logistic function was adapted to fit the NDVI trajectories drived from 1Km resolution MODIS data, and a strong dependency of vegetation phenology on altitude was found. In another study Sulieman and Elagib (2012) used multitemporal remote sensingdata to map the

[2]http://www.fonterra.com/global/en

effects of climate, land use and land cover changes along three different livestock seasonal migration routes in eastern Sudan. A major conversion from natural vegetation cover to agricultural land is reported along with the significant increase in climate warming (based on 68 years (1941–2009) of climate date e.g., temperature, rainfall and aridity index). Dedicated efforts are being made to fully detect and map the transhumance corridors using both remote sensing and geospatial analysis approaches (Trans, 2014).

In summary, the potential of remote sensing to trace corridors of seasonal movement of herds has been established. More work needs to be done in order to exploit the use of high resolution optical and radar imagery in order to fully uncover the impact of these seasonal movements on vegetation phenology.

Remote sensing of nature conservation grassland sites

For the maintenance of biodiversity in Europe, the European Union has legislated a legal policy framework that includes the Habitats and Birds Directives (EEC, 1997, 1979) which describe the types of habitat (e.g. grassland, forest or meadow types) whose existence is in danger (Natura 2000) and needs to be preserved by the member states (Ali et al., 2013). Since the implementation of these directives,mapping, reporting and monitoring on the status of nature conservation sites has been a key research topic. Over time remote sensingmethodologies and techniques have become more sophisticated, especially for synoptic data acquisition, and are now being successfully used for fast, reliable and consistent mappingof habitats and species(Nagendra, 2001; Nagendra and Gadgil, 1999). Most conservation sites, including grasslands, are small in size, therefore very high-resolution imagery is required to monitor them, and some of the very high-resolution spaceborne instruments with a short revisit time of a few days, launched within the last decade have been proven suitable for this application(Schuster et al., 2015).

The nature conservation sites are monitored using both multispectral optical and SAR imagery, and increasingly a combination of both. Optical sensors have a long legacy of use in identification of location and changes in habitats (Velazquez et al., 2008), knowledge and object based classification mapping of Natura 2000 species (Förster et al., 2008, 2012) and for assessingclimatic influences on Natura 2000 habitats (Förster et al., 2014). Multi-temporal high resolution RapidEye data have proven particularly useful in deriving phenological vegetation dynamics from time series imagery, where at least three acquisition dates within a year are available (Franke et al., 2012). Since the launch of the very high-resolution TerraSAR-X and COSMO-SkyMed SAR sensors, protected sites can also be monitored using radar imagery, with recent studies by Ali et al. (2013) and Schuster et al. (2011) demonstrating the potential of both sensors for successfully identifying grassland management practices in protected sites. Although the combined use of SAR and optical data has not yet been explored in detail, Ali et al. (2013) highlighted the potential use of both data sources for cross validation.

Vanden Borre et al. (2011a, 2011b) conducted a detailed review of the legal requirements for Natura 2000 habitat monitoring requirements and practices, and how remote sensingis being used to fulfil this task. In order to enhance the utilization of remote sensing technology, field experts and conservation site managers suggested that the prime focus must be on data standardisation, development of user-friendly products, method validation and knowledge sharing. Since their review, work has been ongoing to resolve these issues, for example, Schröder et al. (2013) stress the need for pre-validation of Earth observation products for Natura 2000 sites before delivery. On the other hand, Nieland et al. (2012) are working on an ontological approach for the integration of classification methodologies in order to overcome the issues of scale and the transferability of methodologies. While these studies address all conservation sites, the challenges raised apply equally to grasslands, and the need for

common data standards and methods, and accessible products for a range of end-users are of relevance to all aspects of grassland management.

In summary, the applicability of multispectral and multitemporal remote sensing data for both monitoring and mapping of grassland conservation sites has been demonstrated. More research is required to overcome the limitations of site specific methodologies (Schuster et al., 2011) in order to make them more robust and standardised. These sites are typically small in size, so high resolution hyperspectral remote sensing data can be used to better explore species compositions. Application of SAR data in cloudy conditions is equally feasible as demonstrated by Ali et al. (2013).

OPERATIONAL AND TECHNICAL CHALLENGES

Overall in the domain of remote sensing the research focus for classification and retrieval of biophysical parameters is now shifting towards the application of machine learning algorithms.Object-based image classification presents a paradigm shift to gain a new perspective on image classification and better follow the boundaries of natural vegetation elements. In object-based classification, segmentation scale and classification accuracy are strongly linked(Liu and Xia, 2010), and careful selection of segmentation scale is required. Machine learning strategies are becoming more widely used within the remote sensing community, and methods like random forest and extremely randomized treesare now widely evident in the literature(Barrett et al., 2014). In future,approachessuch as deep learning and data assimilation will provide more insight into the integration of multisource remote sensing data for complex and dynamic environmental systems. These methods are based on supervised learning, and thus training data are required for classification and parameter retrieval applications. Machine learning algorithms are data driven and their performance is highly influenced by the number of features, sample size and data pre-processing steps. Until

recently it was a challenge to build a sufficiently long time series for machine learning applications,especially for multi-temporal analysis. For example remote sensing data from Landsat and MODIS are available for longer periods of time, but in situ or inventory data are available only for selected sites, which limits the national or global scale evaluation using these methods.

Until recently, optical sensors were considered the best data source for mapping and monitoring small-scale variations within and among the fields due to their high spatial and spectral resolution.However, following the launch of high-resolution microwave radar remote sensing satellites (e.g., TerraSAR-X, COSMO-SkyMed, Radarsat, Sentinel-1) the application domain of radar sensors has widened. For example the TerraSAR-X Staring Spotlight acquisition mode can acquire images with a spatial resolution of up to 0.25m every 11 days. Achieving this high resolution from space can further support precision agriculture developments, especially for areas under persistent cloud cover.

High-resolution radar remote sensing data with an improved temporal resolution will help to monitor crop health and will provide a mechanism for timely crop yield estimation, while in case of grasslands it can be used for monitoring grassland management practices as shown in Figure 3. Spatial resolution is a crucial component in remote sensing applications, especially for quantitative scientific analysis, and as Figure 3 demonstrates inter and intra paddock/field variations can be detected using radar data, highlighting different agricultural states. Using high-resolution sensors(e.g., TerraSAR-X, Radarsat, COSMO-SkyMed) it is possible to detect many management related activities for example grazing herds, hedges and cultivation. It is also possible to trace the identify poorly performing patches of the field using multi-temporal acquisitions,but the major challenge and limitation remains inthe high data acquisition cost of the highest spatial resolution sensors, and their small area coverage. Currently most of the radar remote sensing sensors (with some exceptions) are single or dual

channel, and polarisation limited to two directions, but as the technology matures further future radar sensors will potentially provide additional information for more reliable methods for agricultural monitoring.

Thus, for both optical and radar remote sensing the major limitation is the compromise between spatial resolution and spatial coverage. For example TerraSAR-X Staring Spotlight mode has the highest illumination time and spatial resolution (up to 0.25m) but the smallest swath size (4Km (width) x 3.7Km (length)), compared to the Spotlight mode (spatial resolution up to 2m: 10km (width) x 10km (length)),Asimilar comparison is true for WorldView and MODIS, where high spatial resolution is achieved at the cost of swath size.

Farmers in every region follow different management strategies i.e., amount of fertilizer, use of pesticides, grazing season length, and measuring units (kg/tonne dry matter per hectare, kg/tonne dry matter per acre). With this diversification in management practices there are challenges in building a robust and transferable classification and reporting scheme (Figure 4 gives an over of different remote sensing techniques their potential scope and limitations). In future, as more sensors are launched it is important for the community to develop a uniform standardized and transferable approach for monitoring farms at different geographical scales. For the transferability of methods it is very important to have a uniform input dataset, and one potential solution for this could be the development of a new ontology based data collection and standardization framework asundertaken by the biology community(Bard and Rhee, 2004).Additionally, the remote sensing community must continue to advocate the launch of follow-up missions of imaging satellites in order to ensure long term consistent monitoring.

There is a need to train and educate the end users (farmers, land manages and policy makers) about the potential applications of satellite remote sensing, and with standardised methods this is more achievable. Current technical and scientific deliverables (e.g. project reports,

scientific publications) output from many research projects further discourage communication between the data providers and end users. One option could be forscientiststo develop more portable (i.e., WebGIS) and accessible (mobile apps) solutions, which are readily available to the end users (e.g., PastureFromSpace Australian project). The benefits offered by remote sensing scientists working with those in the agricultural community will not only help to generate more business, but also to widen the scope and application domain that can be achieved through the use of imaging satellites.

DISCUSSION AND FUTURE PROSPECTS

In conclusion, grasslands are one of the most widespread landcover types found globally, and they need to be monitored at multiple scales (gobal, regional, national, paddock) depending on the nature of the information required.Given the small–scale coverage of traditional ground–based methods of grassland monitoring, satellite remote sensing approaches are likely to be a significant contributor to future operational studies. Different sensor specifications are required depending on the application scale, for example, for global scale applications a sensor with large spatial coverage and coarse resolution (i.e., MODIS, AVHRR) would be sufficient.In the case of managed grassland related applications (at paddock scale) sensorswith high spatial and temporal (GeoEye: 1.35m, 3 days; RapidEye: 6.5m, 5.5 days; QuickBird: 2.4m, 1–3.5 days) resolution are the preferred choice. During the growing season temporal resolution is very important and plays a critical role in near real-time monitoringof phenological stages, and when combined with very high spatial resolution imagery,inter- and intra-field variations can be detected.Thus, despite some instrument biases (Yang et al., 2013) satellite sensors currently present the best option for long term, large scale, objective and repeatable studies.

Optical sensors are more appropriate for grass monitoring and mapping compared to radar data (Price et al., 2002; Smith and Buckley, 2011) at present, given the difficulty in relating radar backscatter to grassland properties(Hajj et al., 2014), but this may change with the advent of very high resolution fully polarimetric SAR sensors. Different VIs derived from optical remote sensing data correlate well with different vegetation biophysical parameters, but the biggest challenge to the use of optical imagery is cloud contamination and atmospheric noise. Data cleaning, by filtering or use of a cloud mask to remove noisy pixels is widely undertaken, but is very sensor specific and location dependent. The conservation of image information and removal of noisy signals is complex, and in order to construct a long time series of reliable values the most commonly used approaches are time-series composites and the integration of multi-sensor data. However, this latter approach is hindered by variable instrument biases, spectral response signals and spatial resolutions. Poorly designed data fusion algorithms that assimilate different datasets might also result in high uncertainty in the final output. On the other hand, modelling approaches driven by satellite remote sensing have proven to be a robust method for deriving grassland information, but the availability of high quality validation data to accurately calibrate the model can be a limiting factor as it requires a collection of sufficient high quality validation samples at large scales both expensive and laborious. Careful selection of sensors (especially in terms of spatial and temporal resolution) for data acquisition is also very important, for example frequently acquired and freely available hypertemporal remote sensing data (e.g. MODIS) are widely used to generate time composites and thus overcome cloud contamination issues, but they cannot be applied for field level mapping and monitoring in many countries due to the coarse resolution whereby the pixel size is greater than field size.

To achieve the maximum benefit from satellite remote sensing for grassland related activities a number of issues have been identified.

Classification is a classical application of satellite images, and currently the focus is shifting from statistical to machine learning approaches, due to their ability to better identify the relative importance of different inputs as well as learn from repeated use. Classification of grassland types and formations using satellite remote sensing data has been tested by using different classifiers and sensors in different regions of the world. In addition to local, regional and national scales, an acceptable classification accuracy using medium resolution (Landsat TM/ETM+) data has been achieved at the global scale (Gong et al., 2013), however such an approach is very data and computationally intensive. Individually machine learning and object based classification methods perform very well but, in future, these two approaches may be further integrated to exploit the benefits of each, for example a random forest random field $(RF)^2$classifier (Payet and Todorovic, 2010).The literature suggests that random forest and extremely randomized trees classifiers have the best potential and offer improved classification results for grassland identification, but further work on these methods is needed to validate new high resolution optical and SAR data and explore the transferability of these methods.

Maximum separabilityofspectrally similar classes, such as different grassland types, can be achieved with a larger number of narrowband images,but currently the scope of spaceborne hyperspectral remote sensing is very limited due the fact that Hyperion is the only operational satellite. More detailed analysis is still to be done on the potential for grassland mapping and monitoring from spaceborne hyperspectral data, but this is unlikely to progress prior to the launch of EnMAP which has 244 spectral bands (scheduled for 2017). The use of hyperspectral data for grassland classification using machine learning classifiers has not been fully explored but studies using airborne hyperspectral remote sensing data (Chan and Paelinckx, 2008; Yang and Everitt, 2010; Darvishzadeh et al., 2011) suggest the potential and feasibility of the application of spaceborne hyperspectral remote sensing data for grassland

mapping. In future this might result in a paradigm shift in sensor development from multispectral to hyperspectral constellations.

The advantage of using fully polarimetric SAR data over dual and single polarizations in terms of improvement in classification performance is well established (Lee et al., 2001). The inconsistencies reported in the literature (Dusseux et al., 2014; Smith and Buckley, 2011) indicate that SAR polarimetry applications to grasslands still require more detailed investigation as an understanding of SAR polarimetry theory matures and the availability of spaceborne fully polarimetric data increases. In coming years, especially after the launch of SAOCOM–1/2 (an Argentinian constellation of two L-band SAR sensors scheduled for launch in 2015) and the RADARSATConstellation mission (three Canadian C-band SAR sensors, scheduled for launch in 2018), a better understanding of the potential for fully polarimetric SAR data to analyse the back scattering behaviour of different habitat types at different polarizations will be possible.As a result, a more reliable delivery of grassland products in cloudy regions should be possible.

The application of very high resolution data for remote sensing based precision agriculture approaches to grassland is now evolving to the same level of maturity as experienced by arable agriculture. As more very high-resolution sensors are launchedand work is done on data standarisation more reliable operational satellite based grassland management tools are expected. Furthermore, operational tools that are simple to understand and operate for non–experts, such as websites or mobile applications that retrieve information from a dedicated data center server could become a more common practice across precision agriculture for all land cover types.

Much of the research that has been done on grasslands has exploited multi-temporal datasets, with relatively few long term studies done except those which could exploit information content from Landsat or MODIS datasets. Additionally, hypertemporal time series that are

optimised to minimise the computational load,can enhance grassland classification, especially where there are rapid or distinctive phenological changes through the growing season. To have a consistent time series of data over many years to track long term changes in land cover, and especially for operational purposes, a commitment to continuity missions is required.MODIS is providing free data at different spatial scales for more than a decade. Suomi National Polar-orbiting Partnership (NPP) equipped with five sensors including Visible Infrared Imaging Radiometer Suite (VIIRS) was launched in 2011. Spacecraft orbits the Earth 14 times a day. VIIRS has the spatial resolution of 375m and 750m for Imagery and Moderate resolution bands respectively. NPP VIIRS data will be used to expand upon the MODIS applications to land, ocean and air quality. The VIIRS data will also be freely available to the public unlike Rapideye and Quickbird hyper-spatial data, which is not easily accessible and are expensive for developing countries and large scale applications. Sentinel-2 will also provide a comparable dataset to the Landsat and SPOT missions in the optical part of the spectrum, and at radar wavelengths Sentinel–1 will provide C–band SAR data following ERS1/2 and ENVISAT ASAR, and a TerraSAR-X2 launch is planned in 2016 as a follow–up mission of TerraSAR-X (Janoth et al., 2012).

Despite the complexity of grassland ecosystems, this review has demonstrated that satellite remote sensing technologies have been proven as effective tools for monitoring, mapping and quantifying different grassland types and biophysical parameters. Use of optical remote sensing data is the most prevalent in the literature, while the use of SAR or a combination of SAR and optical data has been less widely reported, although this will increase as more SAR missions become operational in the coming years.

SUMMARY

To conclude this review paper:

Satellite remote sensing can be used for the retrieval of grassland biophysical parameters, including biomass, quality, growth, land cover, degradation, grazing capacity, as well as mapping and monitoring for conservation and management.

Optical sensors have been most widely used given the good understanding between reflectance and vegetation properties and the difficulty in relating radar backscatter to grassland biophysical properties, but this may change with the advent of very high-resolution fully polarimetric SAR sensors.

The use of hyperspectral data for grassland classification using machine learning classifiers has not been fully explored but studies using airborne hyperspectral remote sensing data suggest the potential and feasibility of the application of spaceborne hyperspectral remote sensing data for grassland mapping, and with future hyperspectral sensors this potential may be realised.

The application of very high-resolution data for remote sensing based precision agriculture approaches to grassland is now evolving to the same level of maturity as experienced by arable agriculture, but more work needs to be done on communicating the benefits and opportunities of space to the farming community.

Hypertemporal time series that are optimized to minimize the computational load, can enhance grassland classification, especially where there are rapid or distinctive phenological changes through the growing season

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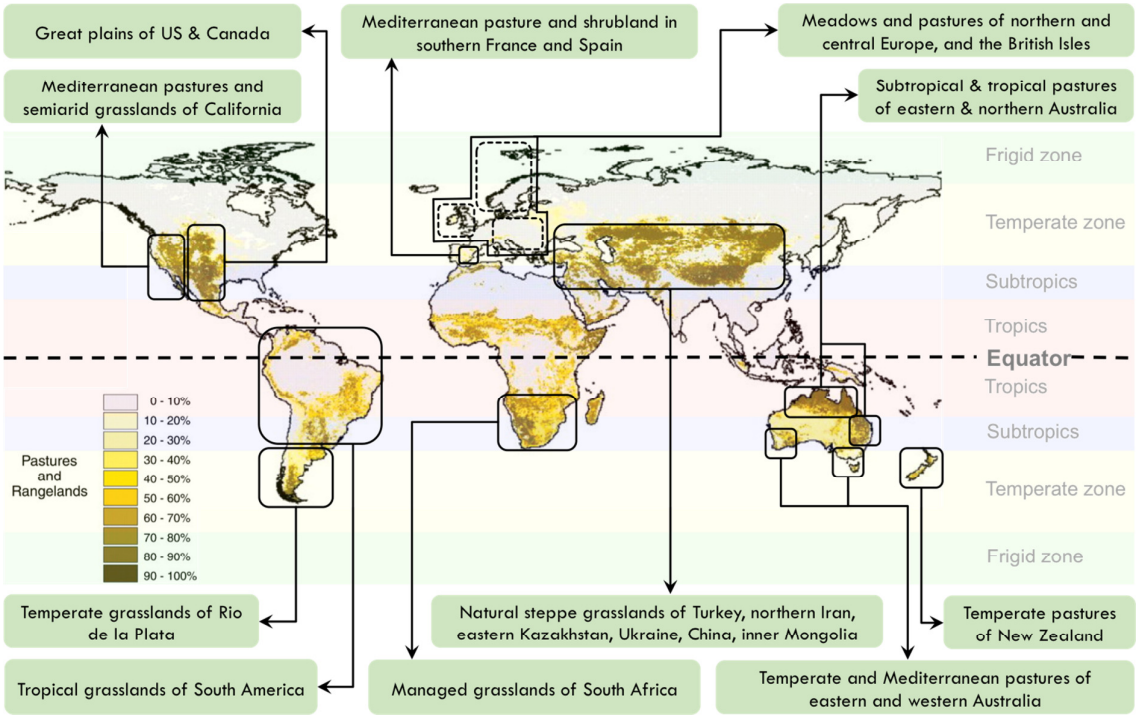

Figure 1. Overview of the global extent of pastures/grasslands [Modified fromFoley et al. (2005), grey boxes are themajor managed pastures, grasslands and rangelands areas (Hill, 2004)].

Figure 2. Spatial resolution comparison (false colour composite: R = NIR, G = RED, B = GREEN) among QuickBird (A), RapidEye (B) and Landsat–8 (C) covering a managednatural grassland conservation site west of Berlin, Germany (Courtesy: Dr. Michael Förster).

Figure 3 TerraSAR-X Staring Spotlight color composite (R: 08-06-2014, G: 19-06-2014, B: 11-07-2014) of Teagasc Curtin Farm. Potential of very high-resolution microwave radar (TerraSAR-X) data: (A) Monitoring of hedges and individual tree count, (B) furrow/plough lanes, (C) possibility to detect the location of grazing herds if they are standing close to each other, and (D) inter and intra paddock variation.

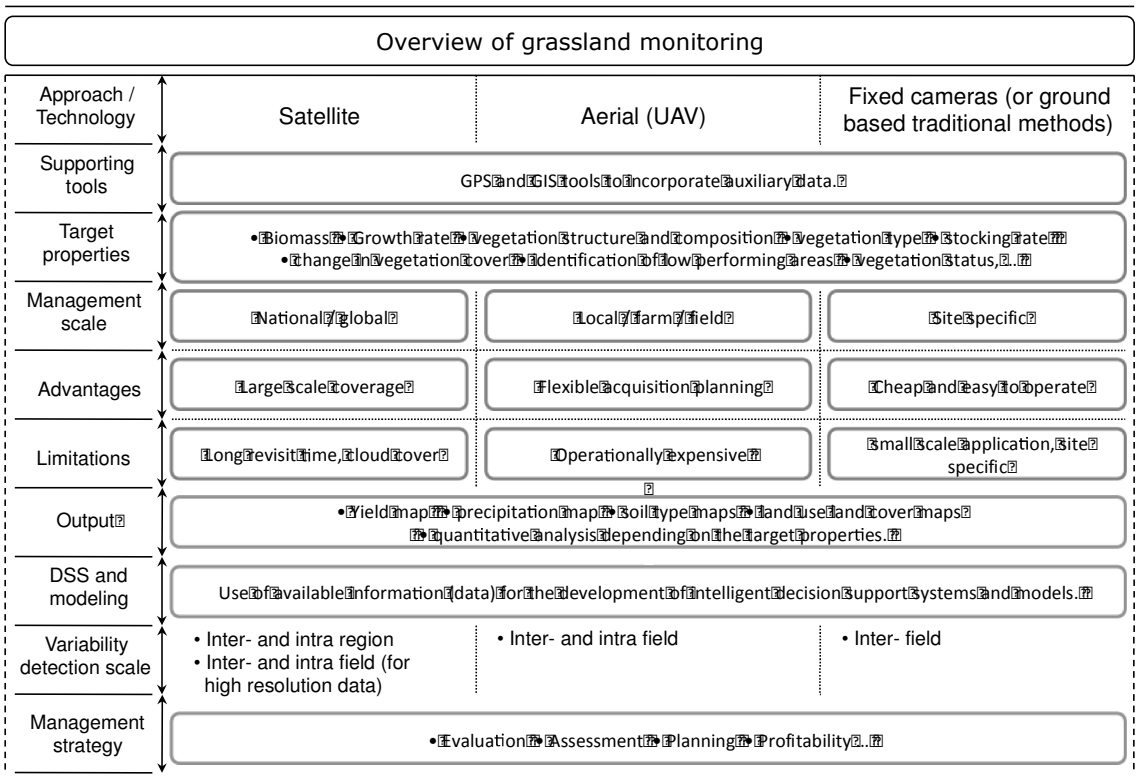

Figure 4 An overview of grassland monitoring technologies with their limitations and scope.

Table 1 Comparison among ground-based methods.

Methods	Scale	Benefits	Limitations	Category
Visual	Field/paddock–farm	Fast and cheap.	Need specific expertise, vague estimation.	Non-destructive
Clipping		More accurate than visual assessment.	Time consuming if large number of samples are required.	Destructive
RPM		Esay to operate and cheap.	Time consuming.	Non-destructive
Field spectrometry		Information on other biophysical parameters can also be retrieved.	Trained operator and post processing is required.	Non-destructive

Table 2 Grassland mapping/classification using satellite remote sensing data (examples from literature are grouped according to the classifiers used)

Classifiers	Examples	Advantages	Disadvantages
Unsupervised	Gu et al., (2013); Wen et al., (2010)	It is simple and easy to implement. Training (prior knowledge) data is not required for classification. It is unbiased, as clustering is purely based on pixel values.	Does not consider the spatial relationships in the data and spectral classes do not represent the on ground features. Post classification interpretation can be very time consuming.
Maximum likelihood	Baldi et al., (2006); Miehe et al., (2011); Reiche et al., (2012); Toivonen and Luoto, (2003); Weiers et al., (2004)	Until recently it was the most popular and widely used supervised classification approach. The pixels are classified based on their probability of belonging to a class and if the probabilities are not same for each class 'weight factors' can be specified. It is accurate for normally distributed datasets and considers variability in the data.	In the case of large data sets classification is extremely slow. Classification results can be biased for small training samples. Normally distributed data assumption is not always true, and this might result in misclassification.
Object based classification	Brenner et al., (2012); Franke et al., (2012); Peña-Barragán et al., (2011); Tovar et al., (2013)	It can utilize the spatial information (i.e., shape, size, color, compactness) of high resolution data, and provide high accuracy.	High computational cost. Accuracy depends on segmentation process for example scale selection, which is not well defined
Principal component analysis	Hill et al., (2005, 1999)	Reduces the data dimensionality and enhances the key features in the data. The new 'components' might detect the variations/changes.	Assumes multi-temporal data are highly correlated, and makes very strong assumptions that the directions with the largest variance contain most of the information.
Decision tree	Dubinin et al., 2010; Peña-Barragán et al., 2011; Wang et al., 2010; Wen et al., 2010)	Simple to understand and to interpret. Trees can be visualized. Requires little data preparation. Fast and able to handle both numerical and categorical data.	Decision-tree learners can create over-complex trees that do not generalize the data well and trees can be biased if some classes dominate.
Machine learning	Filippi and Jensen, (2006); Lawrence et al., (2004); Masocha and Skidmore, (2011)	Often much more accurate than human-crafted rules as they are data driven. Automatic method to search for hypotheses explaining data. Flexible and can be applied to any learning task. Rich interplay between theory and practice, with improved results as datasets increase.	Data–driven methods need a lot of labeled data, requiring extensive ground truth datasets. Typically require some programming knowledge.

Table 3 Grassland yield estimation using satellite remote sensing data (examples from literature are grouped according to the models/methods applied)

Models/methods	Sensor	Examples
Linear regression	Landsat TM/MSS/ETM+, IRS, SPOT VEGETATION, SPOT 4/5, Hyperion, NOAA/AVHRR,	(Bradford et al., 2005; Han, 2001; He et al., 2009; Kurtz et al., 2010; Loris and Damiano, 2006; Prince, 1991; Psomas et al., 2011b; Verbesselt et al., 2006; Williamson and Eldridge, 1993; Wylie et al., 2002)
Exponential regresssion	Landsat TM, MODIS	(Xu et al., 2008, 2007), Huang et al. (2013)
Optimal regression model	MODIS, Landsat TM, NOAA/AVHRR	Yu et al. (2010), Jianlong et al. (1998)
Power regression	MODIS	(Xu et al., 2008, 2007)
Logrithmic regression	ERS-SAR, IRS, SPOT-5	Vescovo and Gianelle. (2008), Moreau and Le Toan. (2003)
Advantages:	The principal advantage of empirical modelling is its simplicity, availability, interpretability and acceptance among the scientific community.	
Disadvantages:	In nonlinear dynamic environment, the data from chaotic systems do not corrspond to the strong assumptions of a linear model. These models do not havea physical basis and mostly used for site specific analysis or model development.	