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Review

Remote sensing based indicators of vegetation species for assessing rangeland degradation: Opportunities and challenges

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Rangeland degradation is a serious hindrance to sustainable development in degraded areas. Mapping and monitoring vegetation species is an increasingly important issue across various fields of rangeland management. Remote sensing technology is a tool for mapping and monitoring vegetation species and it provides timely and relatively accurate information concerning degradation in biological rangeland resources. The objective of this review was to provide precise and essential information relating to the application of both multispectral and hyperspectral sensors as well as to their limitations with regard to mapping and monitoring rangeland degradation based on the abundance and distribution of vegetation species and algorithms used to process remotely sensed data when classifying these species. The abundance and distribution of the different vegetation species can be used to indicate the gradient level of rangeland degradation. It can be concluded, that up-to-date, spatial information and appropriate processing techniques are essential requirements for extracting increaser and decreaser spectral information that can be used for sustainable rangeland management.

Key words: Remote sensing, rangeland degradation, increaser and decreaser species, indicator, vegetation indices.

INTRODUCTION

Rangeland is an important natural ecosystem that offers a habitat for wildlife, grazing areas for domestic stock, and goods for local communities (Kawanabe et al., 1998). Rangeland degradation has been identified as being one of the most serious global environmental issues that needs to be addressed (Hill et al., 1995; Kassahun et al., 2008). Rangeland degradation can be defined as a loss of quantity and quality of the material produced for grazing for a particular livestock species in arid and semi-arid areas as a result of human activities and natural factors (Oba and Kaitira, 2006; Solomon et al., 2007). Human causes of rangeland degradation are: overstocking, the expansion of cropped areas, uprooting of range shrubs off-road driving, increased fires, water scarcity and poor land use management and planning. Natural causes include changes in climate elements and soil properties (Al-Karablieh, 2010; Eswaran et al., 2001; Hoffman and Todd, 2000; Solomon et al., 2007). Rangeland degradation can usefully be considered in terms of types of grass communities and the production characteristics of different grasses, particularly, their grazing value (Tainton, 1999). Rangeland plant quality and quantity have been successfully used as indicators for mapping, monitoring and classifying rangeland

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degradation in degraded areas (Klein et al., 2007; Reed and Dougill, 2002). This is because, some plant species are well adapted to specific growth conditions and their quality and quantity characteristics may change dramatically if these conditions change (Van den Berg and Zeng, 2006; Van Oudtshoorn, 1992).

Grasses are classified into three categories (that is, increasers, decreasers, and invader) based on their grazing value and the changes in their relative abundance in the presence or absence of grazing (Dyksterhuis, 1948, 1949). Decreaser species are the dominant species in flourishing rangelands, but they diminish when rangeland deteriorates through overutilization or underutilisation (Hardy et al., 1999). Increaser species, by contrast, flourish in rangelands that are overgrazed or underutilised, and the abundance of these species is therefore an indicator of the poor condition of rangeland (Dyksterhuis, 1949; Van Oudtshoorn, 1992). The assessment of rangeland degradation based on the abundance and distribution of decreaser and increaser species has been successfully evaluated and classified (Tainton, 1988; Trollope et al., 2008; Van Oudtshoorn, 1992).

Mapping the extensively degraded rangelands requires the use of conventional survey methods, such as local expert knowledge and field observation to provide accurate information on the spatial distribution of grass species. These methods provide significantly better results when it comes to mapping species over small geographic areas. However, these conventional field-based methods require visual estimation of species percentage as well as intensive fieldwork, which includes the identification of species characteristics. Such undertakings are both costly and time-consuming, because rangelands usually cover large expanses that are, moreover, situated in isolated and inaccessible areas (Harris, 2010; Tromp and Epema, 1998). On the other hand, the remote sensing techniques to map the spatial distribution of grass species over large geographic areas of degraded rangeland have attracted scientific attention, resulting in the provision of different spatial resolution imageries that are not only feasible and cost-effective, but that also provide timely and accurate information (Lees and Ritman, 1991; Shoshany, 2000; Tromp and Epema, 1998; Ustin et al., 2009). The advancement in remote sensing comes up with high-resolution hyperspectral data that provide a significant enhancement of spectral measurement capabilities for investigating the most powerful contiguous and narrow wavelengths (less than 10 nm) throughout the ultraviolet, visible and infrared portions of the electromagnetic spectrum (Kumar et al., 2001; Thenkabail et al., 2004). These narrow spectral wavelengths allow the identification of characteristic spectral attributes for the mapping and monitoring of vegetation at species levels in different ecosystems (Thenkabail et al., 2004; Zwiggelaar, 1998). In spite of the great capability of remote sensing to provide detailed spectral information, the mapping of vegetation species using hyperspectral remote sensing data is challenging due to data dimensionality, data processing, and the fact that the images are too prohibitively expensive to use (Metternicht et al., 2010; Okin et al., 2001; Pinet et al., 2006; Schmidtlein and Sassin, 2004; Underwood et al., 2003). However, multispectral data is relatively available, at a low cost, and does not require complex preprocessing and processing techniques. Considering these advantages, the use of multispectral data should be operationalised and implemented in order to provide accurate and up-to-date information on mapping vegetation species over large areas. However, mapping vegetation in degraded areas at species level using multispectral data, such as Landsat thematic mapper (TM) and SPOT imagery is challenging, because of the low spectral resolution of sensors and spectral overlap between the vegetation species (Harvey and Hill, 2001). The development in multispectral sensors, such as WorldView containing key spectral bands, has brought about unique opportunities for those wishing to classify vegetation at species level (Dlamini, 2010; Omar, 2010). Multispectral and hyperspectral data have been used for several decades in mapping vegetation communities in degraded ecosystems (Schmidtlein and Sassin, 2004; Tromp and Epema, 1998; Vogel and Strohbach, 2009).

Previous reviews concerning the application of remote sensing techniques in rangeland degradation have been done. Lass et al. (2005) investigated the use of hyperspectral remote sensing of invasive species detection. Metternicht et al. (2010) reviewed the potential use of remote sensing for assessing and mapping different indicators of land degradation. Shoshany (2000) reviewed the utility of spectral, temporal and spatial data for identifying Mediterranean vegetation land regions and the limitations of multispectral applicability. Pinet et al. (2006) reviewed the possibilities of using imaging spectroscopy for monitoring land degradation and desertification. Hill et al. (1995) discussed the potential use of multispectral remote sensing for mapping and monitoring land degradation in Mediterranean environments. Based on the results of the aforementioned studies, the human and physical factors causing rangeland degradation are thought to be severe overstocking and climate change, respectively. The application of multispectral and hyperspectral remote sensing techniques provides accurate and timely information for mapping and monitoring vegetation cover. The shortcomings of the aforementioned studies are that no specific review has focused on the application of multispectral and hyperspectral remote sensing techniques for mapping and classifying the increaser and decreaser species as indicators of different levels of rangelands condition.

This study reviews the research results concerning the application of both multispectral and hyperspectral remotely sensed data for vegetation species discrimination. The specific objectives of this study were: (1) to review discriminating and mapping vegetation species in degraded rangelands; (2) to highlight the advancement in remote sensing technologies in terms of spectral bands and critical band settings and their capabilities for classifying vegetation species within a complex rangeland environment; and (3) to highlight the major challenges still involved in remote sensing and suggest what further research is needed for the successful application of remote sensing in mapping vegetation species in degraded areas.

ASSESSING AND MONITORING RANGELAND DEGRADATION USING DIFFERENT TRADITIONAL FIELD-BASED METHODS AND APPROACHES

Rangeland condition is measured to evaluate the rangeland productivity and plan management interventions (Passmore and Brown, 1991; Paudel and Andersen, 2010; Peden, 2005). Numerous efforts have been made to assess and monitor rangeland degradation using various methods and approaches, such as expert opinions, herder knowledge, focus group discussions, land users' opinions, benchmarks, basal cover, Shannon's diversity index, observations and measurement of soil properties, and estimates of productivity changes (Moyo et al., 2008; Oba and Kaitira, 2006; Oluwole and Dube, 2008; Stringer and Reed, 2007). Oba and Kaitira (2006) used the herder knowledge approach to evaluate the communal rangelands in Maasai grazing territory in Northern Tanzania. The method was based on the relative abundance of increaser and decreaser species. Their results showed that herder knowledge approach can be used to classify the rangeland into the following different levels: non-degraded, stable and degraded. Moreover, the herder knowledge method provides a quick way of understanding the current status of the rangelands. Unfortunately, due to the herders' migratory behaviour, the challenge was how to engage them in participatory research.

In the Eastern Cape of South Africa, Oluwole and Dube (2008) assessed the utility of the benchmark method, the basal cover technique, and soil analysis to evaluate rangeland condition. Their results demonstrated the feasibility of using the benchmark method, the basal cover technique, and soil analysis, as these three methods were able to classify the condition of the rangeland into non-degraded, moderately degraded, poorly degraded, and extremely degraded. Stringer and Reed (2007) used land users' opinions to evaluate soils (erosion, fertility and productivity) in Botswana and Swaziland. They concluded that combining local and scientific knowledge can enhance rangeland degradation assessments at national and regional levels. The expert opinion method (for example, indicators, questionnaires, interviews and focus groups) was developed by Jones et al. (2003) to assess the causes, degree, extent and impact of rangeland degradation in Europe. The study produced reasonable results for rangeland degradation assessment using the expert opinion method. However, because some respondents did not reply, or the replies of others were incomplete, the results were difficult to use when comparing regions. However, most of the aforementioned scientists utilised these methods in the assessment of commercial rangeland. The usefulness of such methods for assessing communal rangelands is less well established (Reed and Dougill, 2002). Moreover, such methods tend to be economically inefficient, time consuming and labour intensive, and are sometimes impossible to accomplish due to the fact that rangelands cover a large spatial extent and are difficult to access (Reed and Dougill, 2002; Peterson et al., 2002). The remote sensing technique offers quick and repetitive data (including detailed information on vegetation status) and is accurate and potentially inexpensive, and could thus, successfully evaluate rangeland degradation in a large region (Tanser and Palmer, 1999; Wessels et al., 2008). Although, the previous studies produced reasonable results with regard to mapping rangeland degradation based on vegetation communities using conventional field-based methods and remote sensing, more attention needs to be given to the issue of how to improve the accuracy of mapping increasers and decreasers at species level in order to identify different levels of rangeland degradation.

SPECTRAL PROPERTIES OF VEGETATION SPECIES IN DEGRADED AREAS

In degraded environments that are characterized by sparse vegetation species and the spectral effects by soil background, a careful consideration should be given to the spectral properties (Hill et al., 1995). Sunlight is the main source of energy for several biological activities taking place inside the plant cells (Ustin et al., 2009). When light interacts with the vegetation surface, it can be reflected, absorbed, and/or transmitted due to different materials on the earth's surface. An understanding of the spectral behaviour of increaser and decreaser species is essential for the interpretation of a remotely sensed image. In general, many efforts have been made to better understand the relationship between light solar radiation and plant leaves. The spectral response of vegetation depends upon the properties of both the incoming radiation (for example, angle of incidence, conditions of radiation and wavelength) and the vegetation (chlorophyll a and b, α-carotene, b-carotene, xanthophylls, protein, oil, water, starches, lignin, cellulose, sugar and nitrogen) (Asner, 1998; El-Nahry and Hammad, 2009). The spectral reflectance of vegetation species in degraded

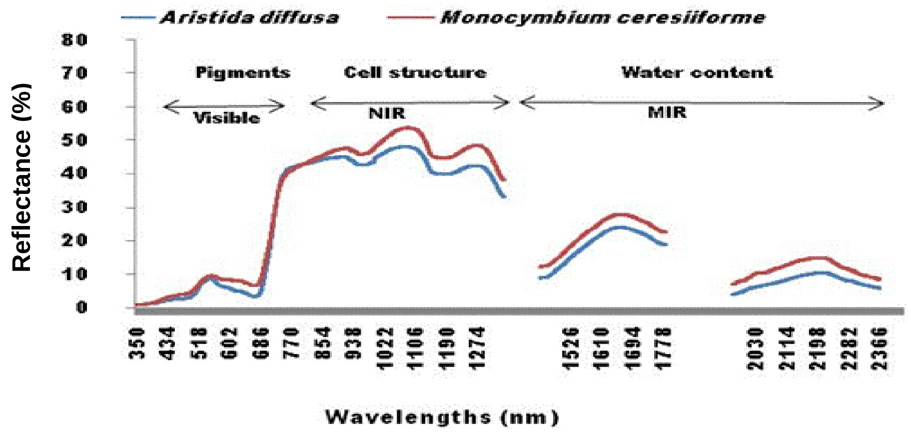

Figure 1. Mean spectral canopy curves for increaser species (*Aristida diffusa*) and decreaser species (*Monocymbium ceresiiforme*) in Drakensberg Montane rangelands with the dominant factors controlling reflectance being displayed.

areas is normally subdivided into three domain regions, namely, the visible (400 to 700 nm), the near-infrared (NIR; 700 to 1300 nm), and the mid-infrared (MIR; 1300 to 2500 nm) (Figure 1) (El-Nahry and Hammad, 2009; Ustin et al., 2009). Vegetation types have low reflectance and transmittance in the visible region due to strong absorption by chlorophyll a and b, b-carotene, α-carotene, and xanthophyll (El-Nahry and Hammad, 2009; Ustin et al., 2009). They have a high reflectance and transmittance in the NIR region because of their very low absorption of xanthophylls, chlorophyll a and b, b-carotene, and α-carotene. Plant leaves absorb only 4% of the radiation and the remaining 96% is reflected and transmitted (Woolley, 1971). In the NIR, a plant leaf will typically reflect between 40 and 50%, while the rest is transmitted, with only about 5% being absorbed (Govender et al., 2009). The limited absorption in this region is aided by dry leaves, primarily cellulose, lignin, and other structural carbohydrates (Asner, 2000; Cochrane, 2000). Ustin et al. (2009) and Cochrane (2000) reported that the internal leaf structure is the dominant factor controlling the spectral response of plants in the NIR region. Also, reflectance in this region is affected by numerous scatterings, including refraction at air-water interfaces and the fraction of air spaces (Ustin et al., 2009). Spectral reflectance is characterised by being much lower in the MIR than in the NIR due to the strong water absorption by the leaves and the minor absorption features of their biochemical content (Hestir et al., 2008). In green leaves, reflectance and transmittance in the short wave infrared (SWIR) are influenced by water absorption (Ustin et al., 2009).

As there has been no specific research on how increaser and decreaser grass species interact with light, detailed investigation into these aspects is needed for a better understanding of the spectral response of vegetation species in degraded areas. The results of such studies could help researchers to develop accurate models describing, for example, the discrimination of increaser and decreaser species, estimations of grazing value in the rangelands based on increaser and decreaser species, and increaser and decreaser species' biophysical characteristics. Scientists working in the environmental conservation field could use these models to develop methods for rangeland management.

APPLICATION OF MULTISPECTRAL REMOTE SENSING IN MAPPING VEGETATION SPECIES IN DEGRADED AREAS

Mapping and monitoring vegetation species in disturbed areas require that there be extensive coverage and that quantitative, timely, accurate and regularly collected information be gathered. All these factors have made the use of remote sensing a powerful tool (Ustin et al., 2009). Since the early 1900s, when the first aerial photographs were taken, aerial photography with low spatial resolution has been considered the first remote sensing technique, being used as a source of information for mapping vegetation cover (Lillesand, 1999; Mumby, 1999). It can be concluded that aerial photography has considerable advantages over satellite-based data because of its availability, low cost, and because the span of the record covers a longer time period (Wentz et al., 2006). However, aerial photography has not been widely used for mapping and monitoring vegetation cover because of the high costs of colour-infrared film and processing, as well as the coarse spatial and low spectral resolutions, which affect the actual mapping of vegetation (Kakembo, 2001; Laliberte et al., 2004). Recently, multispectral remote sensing with different properties (spatial and spectral resolution) and a variety of sensors (Landsat TM, Landsat ETM+ and SPOT) have been used to discriminate vegetation cover in degraded areas (Liu et al., 2004; Sun et al., 2007; Wu, 2008). Wu et al. (2008)

evaluated the potential of multispectral remote sensing by using Landsat images (Multispectral Scanner (MSS) and TM) to classify vegetation cover in the degraded land of MuUs sandy land in China. The maximum likelihood classifier was used. They concluded that Landsat has great potential when it comes to classifying vegetation cover as there was an overall accuracy of 98.4% (Kappa 0.947) for Landsat MSS, and 99.8% (Kappa 0.995) for Landsat TM.

Savanna rangeland degradation in Namibia was classified by Vogel and Strohbach (2009), who used Landsat TM and ETM+ data. The decision tree classifier was also used. Their results show that savanna degradation can be classified into the following six classes: vegetation densification, vegetation decrease, complete vegetation loss, long-term vegetation patterns, the recovery of vegetation on formerly bare soils, and no change with an overall accuracy of 73.4% with respect to the class pairs' accuracies' which ranged from 80 to 100% for producers' and users' accuracies.

The results of the aforementioned studies produced reasonable results for discriminating between vegetation communities on a regional scale when using multispectral data. However, Landsat and SPOT data have proven insufficient for classifying vegetation at species level because of the low spectral resolution of sensors and the spectral overlap between the vegetation species. Also, most multispectral remote sensing data do not have the red-edge region that is insensitive to atmospheric interference and soil background (Vogel and Strohbach, 2009; Wu, 2008). Therefore, the developments in multispectral data (WorldView) and hyperspectral data can be useful for discriminating rangeland degradation based on the spatial distribution of vegetation species (at species level) because of the detailed spectral information that they can provide. More work is needed to improve the classification accuracy of mapping the spatial distribution of increaser and decreaser species.

LIMITATIONS WHEN APPLYING HYPERSPECTRAL REMOTE SENSING TO VEGETATION SPECIES CLASSIFICATION IN DEGRADED AREAS

In the field of remote sensing, hyperspectral remote sensing, also known as 'imaging spectrometry', 'imaging spectroscopy', 'ultraspectral imaging', 'hyperspectral spectroscopy' and 'narrow-band imaging', is a relatively new technology that is currently being used in vegetation studies (Clark, 1999; Mutanga, 2004). Hyperspectral remote sensing has hundreds of narrow, continuous spectral bands between 400 and 2500 nm throughout the visible (0.4 to 0.7 nm), near-infrared (0.7 to 1 nm) and shortwave-infrared (1 to 2.5 nm) portions of the electromagnetic spectrum (Govender et al., 2009). These narrow bands of hyperspectral remote sensing allow for in-depth mapping and discrimination of vegetation species, something that would not be possible with other multispectral sensors (Okin et al., 2001; Pinet et al., 2006; Wang et al., 2010). Spectral absorptions and reflectance changes in the 400 - 2500 nm range of the reflected electromagnetic radiation provide analytical features that can be used to identify vegetation species (Pinet et al., 2006).

Okin et al. (2001) assessed the utility of AVIRIS satellite imagery for accurately discriminating among vegetation types in the Mojave Desert, USA. Multiple Endmember Spectral Mixture Analysis (MESMA) and Spectral Mixture Analysis (SMA) were performed to estimate the proportion of each ground pixel's area that fits with different cover types. They concluded that AVIRIS show low potential for classifying vegetation types with an overall accuracy of only 30% due to low vegetation cover. The ability of HyMap data (0.45 to 2.5 μm) has been tested for discriminating and mapping two invasive species in the California Delta, USA, when using a logistic regression. Their results showed that the HyMap data distinguished perennial pepperweed from pseudoabsence with accuracies of 75.8 and 63.0%, respectively (Hestir et al., 2008).

Discriminating and mapping vegetation degradation at Fowlers Gap Arid Zone Research Station in Western New South Wales, Australia, was also done using random forest by Lewis (2000). In this research, perennial vegetation, chenopod shrubs and trees were selected for classification using the hyperspectral imaging (CASI). An area of less than 25% was discriminated and mapped. He concluded that high-spectral resolution imagery has potential for the discrimination of vegetation cover in arid regions. However, some authors have successfully used hyperspectral remote sensing for mapping arid vegetation. Wang et al. (2010) assessed the utility of hyperspectral remote sensing for mapping dominant vegetation species (*Leymus chinensis*, *Stipa krylovii* and *Artemisia frigid*) in Hulunbeier, China. They concluded that hyperspectral remote sensing has considerable potential for the discrimination and mapping of these species with an overall accuracy of 95%. Spectral classification of grass quality in African rangeland was also done by Mutanga (2005) using the high-resolution GER spectra, which were resampled to the HyMap. In this research, Fisher's linear discriminant function was used to discriminate between groups of *Cenchrus ciliaris* grass, which were all grown under different nitrogen treatments. The results showed that it is possible to classify samples to their respective groups with an overall accuracy of 77.1%.

In general, there are limitations to using hyperspectral remote sensing for vegetation discrimination at species level. These limitations are due to the following: (1) the effects of a large soil background as a consequence of relatively sparse vegetation (Escadafal and Huete, 1991); (2) plant adaptations to the harsh environment that make the spectral reflectance of the same plants different (Ray, 1995); (3) phenological changes as a result of changes in climatic conditions (in particular, rainfall leads to spectral variability of the same species) (Ray, 1995); (4) the possibility of nonlinear mixing due to multiple scattering of light rays, which leads to an overestimation of green vegetation cover (Ray and Murray, 1996); (5) variations in chlorophyll and carotenoid pigments, leaf structure and succulence (Lewis, 2000); and (6) changes in land use and the relative impact of vascular tissue (Asner et al., 2000). Moreover, there are some limitations related to the hyperspectral data which are extremely large and of high dimensionality (Thenkabail et al., 2004). This problem is termed “curse dimensionality” which leads to the “peaking phenomenon” or “Hughes phenomenon” (Hsu, 2007). Hughes phenomenon means that the field samples are insufficient for the classification requirement which makes the estimation of statistical parameters for the classifier performance inaccurate and unreliable (Hsu, 2007; Jackson and Landgrebe, 2001). Therefore, the analysis of hyperspectral data is complex and needs to be simplified by way of selecting the optimum number of bands required for mapping and classifying vegetation species.

Different statistical band reduction techniques for classification of hyperspectral data have been developed. These include discriminant analysis, classification trees, principal component analysis, support vector machines, artificial neural network, partial least square regressions and random forest (Adam and Mutanga, 2009; Bajcsy and Groves, 2004; Filippi and Jensen, 2006; Huang et al., 2002; Lawrence et al., 2006; Mutanga, 2005; Thenkabail et al., 2004).

All the aforementioned studies have shown the potential of hyperspectral data (as opposed to multispectral data) to provide significant improvements in spectral information for discriminating vegetation at species level. More studies for mapping and classifying vegetation species particularly increaser species are needed to build a spectral library for rangeland in degraded areas.

IMPROVING THE CLASSIFICATION ACCURACY OF VEGETATION SPECIES USING THE ADVANCED MULTISPECTRAL SENSORS

As mentioned earlier, there is a limitation to traditional multispectral sensors (Landsat and SPOT) when it comes to increaser and decreaser classification at species level since they can only provide limited spectral information. Considerable efforts have been made to improve the multispectral data characteristics to work within the species classification field. These efforts include advances in sensor technology, the development of spectral vegetation indices, the improvement of classification techniques and the use of multi-sensor imageries (Liu et al., 2004; Sun et al., 2007). The WorldView-2 satellite sensor is a new generation sensor that significantly enhances spectral measurements’ capabilities over those of traditional multispectral sensors (Dlamini, 2010; Kumar and Roy, 2010; Omar, 2010). The 8-bands multispectral WorldView-2 is a new satellite imaging that was launched in October 2009 by DigitalGlobe. It has a high spatial resolution of 2 m (multispectral) and 0.5 (panchromatic) at nadir. The 8 multispectral bands include four conventional wavelengths located at visible region: blue (450 to 510 nm), green (510 to 580 nm), red (630 to 690 nm), and near-infrared region (770 to 895 nm), in addition to four new wavelengths, which are located at the following places: coastal (400 to 450 nm), yellow (585 to 625 nm), red-edge (705 to 745 nm), and near-infrared 2 region (770 to 895 nm).

In Malaysia, Omar (2010) was able to identify ten of the country’s tropical vegetation species using WorldView-2 imagery. Classification techniques such as maximum likelihood and linear discriminant analysis were performed. The findings from this research showed that the most potentially useful information can be used to discriminate among tropical vegetation species with an overall accuracy of 90%. Better discrimination was achieved in the 903 nm (NIR 2), 831 nm (NIR 1), and 724 nm (red-edge) bands.

In Central Swaziland, the new spectral bands of WorldView-2 satellite were tested by Dlamini (2010), who was able to classify two invasive alien plants, namely *Chromolaena odorata* and *Lantana camara*. These results demonstrated that invasive alien plants can be classified using traditional bands (blue, green, red and NIR 1) with a classification accuracy of 95%; the greatest classification accuracies of 99% were obtained using new bands (Coastal blue, yellow, red-edge and NIR 2). Kumar and Roy (2010) used WorldView-2 data to classify the following six agricultural crops in Muzaffarnagar, India: early wheat, ratoon, berseen (fodder), late wheat, sugarcane, and cauliflower. The results showed that the WorldView-2 data was capable of classifying six agricultural crops with accuracies that varied from 93 to 98%. The researchers also found the following important bands for identifying and mapping crops: existing bands 5 (red) and 7 (NIR 1), and new bands 4 (yellow), 6 (red-edge) and 8 (NIR 2).

Research into the classification of vegetation species by way of WorldView-2 data has achieved promising results. However, more research is still needed in terms of the classification of increaser species in disturbed areas. Increaser species classification has inconsistencies due to different species’ responses under different ecosystems, and understanding their ecophysiological mechanisms, therefore, remains unclear. Investigators need to use the capability of WorldView-2 satellite sensors to look at the biochemical and biophysical parameters that can be used to discriminate and monitor increaser species.

IMPROVEMENT OF VEGETATION SPECIES' CLASSIFICATION USING SPECTRAL VEGETATION INDICES

Early remote sensing measurements of vegetation used data collected by different satellite sensors that measured wavelengths of absorbed light (red portion) and reflected light (near-infrared portion) by way of certain pigments in the plant leaves in degraded areas. These portions of the electromagnetic spectrum (red and near-infrared) are the most important in vegetation indices calculation (Ibrahim, 2008). Spectral vegetation indices (VIs) derived from remotely sensed data have become one of the most important information sources for mapping and monitoring vegetation species in degraded areas (Sun et al., 2007). VIs are useful in the following: (1) reducing variations caused by atmospheric conditions, irradiance, sun view angles, canopy geometry, and shading; (2) minimising the effect of soil background on the canopy reflectance (Elvidge and Chen, 1995); and (3) enhancing the variability of spectral reflectance of vegetation (Liu et al., 2004). VIs are calculated based on either multispectral data or on hyperspectral data. The most widely used VIs are the normalised difference vegetation index (NDVI) (Rouse et al; 1974), the simple ratio (SR) (Gitelson and Merzlyak, 1993), and the transformed vegetation index (TVI) (Deering et al., 1975), all of which respond to the variation in the red and near-infrared portions. Other VIs were developed in order to minimise the effects of soil background, atmospheric conditions, canopy geometry, and sun view angles. These VIs include the modified chlorophyll absorption in reflectance index (MCARI) (Daughtry et al., 2000), the transformed chlorophyll absorption in reflectance index (TCARI) (Haboudane et al., 2002), the visible atmospherically resistant index (VARI) (Gitelson et al., 2002), the visible green index (VGI) (Gitelson et al., 2002), the plant senescence reflectance index (PSRI) (Merzlyak et al., 1999), the structure-insensitive pigment index (SIPI) (Penuelas et al., 1995), the modified normalised difference (MND) (Sims and Gamon, 2002), and the soil-adjusted vegetation index (SAVI) (Huete, 1988). Four vegetation indices (NDVI, SAVI, PVI and RVI) have been used to assess rangeland degradation in semi-arid part of the Qazvin province, Iran. The results show that NDVI is a powerful index for assessing the rangeland degradation as compared to other indices (Ajorlo and Abdullah, 2007). Rahimzadeh-Bajgiran et al. (2008) assessed the effectiveness of the AVHRR–NDVI for drought monitoring in Iran. They concluded that the AVHRR–NDVI can be successfully used for drought monitoring such as the vegetation amount and chlorophyll content of the vegetation in the targeted regions. However, the index was unable to timely detect changes in water status, and sensitive to soil background.

Although, different vegetation indices are used in assessing the rangeland degradation, there are still challenges facing the classification of vegetation species in degraded areas where the reflectance is strongly affected by the background of soil as a result of relatively sparse vegetation and atmospheric conditions. More work is needed to develop different spectral indices that could help reduce the effects of soil background and atmospheric circumstances.

OVERALL CHALLENGES AND OPPORTUNITIES IN APPLYING REMOTE SENSING IN DEGRADED ENVIRONMENTS

Rangeland degradation in arid, semi-arid and sub-humid areas is one of the problems that lower the land's productivity in terms of it being able to provide local communities with livelihoods through the grazing of domestic stock and planting of crops. Therefore, monitoring the spatial extent of rangeland degradation offers a means of understanding the nature and causes of this phenomenon. Different indicators have been used to map rangeland degradation by using soil properties and vegetation. Vegetation is an important component of ecosystems and it also serves as an excellent indicator of early signs of any physical or chemical degradation of the land.

The mapping and monitoring of vegetation species using traditional field-based methods, which allow only a small area to be covered, is costly and time-consuming; it is also sometimes impossible to undertake field data collection due to the poor accessibility of the area being surveyed (Rocchini et al; 2010). On other hand, remote sensing techniques offer a practical, near-real-time, rapid, relatively inexpensive and accurate data for mapping vegetation species over large areas (Ustin et al., 2009). Although, considerable progress has been made with regard to mapping and monitoring rangeland degradation based on vegetation species using remote sensing data such as sensor development and data processing, there are still challenges to be met. There are limitations in using multispectral data (that is, Landsat and SPOT) to map and monitor rangeland vegetation at species level, especially in degraded environments (where vegetation is sparse and there is spectral influence by soil background), due to the low spectral resolution of sensors and spectral overlap between the vegetation species. In addition to this, the vegetation species in a degraded environment are different from those elsewhere due to their spatial and temporal characteristics. Spatial variables include species diversity, structural attributes, and biomass, and are influenced by environmental factors such as soil properties, climate change, geology, topography, and the past biogeographic distributions of the species. Temporal variables relate to seasonal phenology and growth stage, and are influenced primarily by climate (drought) and hydrology (flood). Therefore, spectral discrimination between vegetation types in degraded environments is a challenging task because commonly different vegetation types show the same spectral reflectance signature.

In contrast to data from broadband satellite images, narrow bands of hyperspectral remote sensing (<10 nm) and contiguous spectral bands between 400 and 2500 nm occur throughout the ultraviolet, visible and infrared portions of the spectrum (Govender et al., 2009). These contiguous and many narrow spectral bands allow for in-depth mapping and monitoring of rangeland vegetation at species levels (Asner et al., 2000; Lewis, 2000). However, due to the excessive need for sufficient field samples, availability, and the high cost of images in Africa, only a few studies have investigated the potential of using hyperspectral data (Rocchini, 2010; Thenkabail et al., 2004). Yet, in spite of these shortcomings, there is no doubt that the improvements in sensor instruments and analytical methods over the past ten years, combined with an increased knowledge of vegetation biophysical and biochemical properties, has provided important advances in terms of mapping the spatial distribution of rangeland vegetation in degraded areas at species level. More research is needed to enhance our ability to discriminate between increaser species for the purpose of identifying rangeland degradation using the development of new multispectral sensors such as WorldView-2 data. WorldView-2 data, with its capability of new wavelengths (including coastal, yellow, red-edge and NIR 2) to resolve lacking spectral features in the traditional sensors (Landsat TM, Landsat ETM+ and SPOT), offers great possibilities with regard to increaser species classification.

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