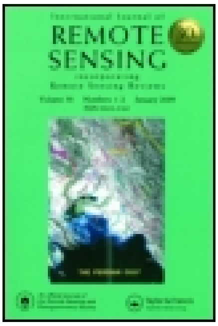

International Journal of Remote Sensing

Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/tres20

Ecological sustainability in rangelands: the contribution of remote sensing

Tal Svoray [a], Avi Perevolotsky [b] & Peter M. Atkinson [c]

[a] Department of Geography and Environmental Development, Ben-Gurion University of the Negev, Beer-Sheva, 84105, Israel

[b] Department of Agronomy and Natural Resources, The Volcani Centre, Bet Dagan, 50250, Israel

[c] Department of Geography and Environment, University of Southampton, Highfield, Southampton, UK

Published online: 28 May 2013.

To cite this article: Tal Svoray, Avi Perevolotsky & Peter M. Atkinson (2013): Ecological sustainability in rangelands: the contribution of remote sensing, International Journal of Remote Sensing, DOI:10.1080/01431161.2013.793867

To link to this article: http://dx.doi.org/10.1080/01431161.2013.793867

International Journal of Remote Sensing, 2013
http://dx.doi.org/10.1080/01431161.2013.793867

Ecological sustainability in rangelands: the contribution of remote sensing

Tal Svoray[a]*, Avi Perevolotsky[b], and Peter M. Atkinson[c]

[a]*Department of Geography and Environmental Development, Ben-Gurion University of the Negev, Beer-Sheva 84105, Israel;* [b]*Department of Agronomy and Natural Resources, The Volcani Centre, Bet Dagan 50250, Israel;* [c]*Department of Geography and Environment, University of Southampton, Highfield, Southampton, UK*

(*Received 17 September 2011; accepted 20 May 2012*)

Rangelands in temperate areas provide food to herds of domesticated animals and, therefore, provide the infrastructure for two major industries: (a) the meat industry that feeds large populations around the globe; and (b) the wool industry that uses fibre from sheep. In the semiarid zone, rangelands have a socio-economic role as they support the economy and culture of pastoral societies. However, despite their importance, rangelands are under constant threat due to encroachment by humans and invasion by noxious plants, due to degradation and erosion processes and due to drought effects. Remote sensing can be used to identify and monitor the threats to ecological processes in rangelands and, thus, to their ecological sustainability. This article provides a review of the scientific literature on the remote sensing of rangelands and discusses recent developments with respect to mapping thematic classes of vegetation and vegetative cover, mapping biophysical properties such as primary production, and monitoring land-use changes, including those driven by anthropogenically enhanced processes such as soil erosion. In the light of the reviewed studies, we expect that future research on monitoring rangeland sustainability with remote sensing will focus on hyperspectral measurements of the spectra of rangeland plant species, on lidar measurements of canopy height, and on synthetic aperture radar for biomass assessment. In the long-term, more predictive (or at least heuristic) modelling of degradation scenarios due to erosion, invasion of noxious species, and land-use transformations can be anticipated.

1. Introduction

Livestock raising on rangelands is a prominent land use in many countries around the world, occupying approximately half of the global land surface (Heady and Child 1994). Due to their large extent, rangelands affect regional biodiversity, global biogeochemical cycles, and energy and gas fluxes (Wallace et al. 2003). Moreover, rangelands, mainly in the form of grassland, but also as shrubland, woodland, and steppe, occupy and therefore protect open areas, their ecosystem functioning, and their food webs. Rangelands provide the infrastructure for the meat and wool industries in temperate zones such as Northern England, Scotland, and central Europe, while in semiarid areas, they support the economy and culture of pastoral, sometimes nomadic, societies (Ginguld, Perevolotsky, and Ungar 1997). Although human use has generally been extensive rather than intensive in most rangelands,

*Corresponding author. Email: tsvoray@bgu.ac.il

human activities have influenced and altered a wide variety of ecosystem characteristics in those areas (Huenneke et al. 2002).

Rangelands provide a diverse battery of ecological services. Foremost, rangelands provide forage, usually for free, which support a high portion of meat production in the world. The availability of forage for herbivores depends on the effective functioning of several ecological, hydrological, and soil processes (Svoray et al. 2008). Adequate management optimizes the long-term productivity and profitability of the rangeland or, in other words, its sustainability. Mismanagement of the rangeland may stimulate soil erosion, interfere with nutrient cycling, and induce degradation in the vegetative community. The main source for forage material, herbaceous vegetation, is often suppressed by more competitive woody plants, agricultural crops, and by over-grazing and drought years. Diminished productivity in rangelands can lead to degraded lands or to land-use transformation into urban or agricultural areas (Shoshany and Goldshleger 2002). However, in addition to ecological outcomes, rangeland productivity and health also provide cultural services: high biodiversity, aesthetics, touristic opportunities, and local identity. These aspects have been recently incorporated into monitoring schemes and international agreements (Flather and Sieg 2000; Maczko et al. 2004).

From the economic point of view, the sustainability of rangelands depends on the price of meat, cost of maintenance of herds and plots, salaries, and the availability of human resources. An imbalance between income and expenditure may threaten the economic sustainability of rangelands. From the social viewpoint, there is an ongoing question concerning the desire to maintain and support rangelands for public benefit, especially given increases in population density, urbanization, and decreases in the availability of, and access to, open areas. However, despite the importance of socio-economic forces and the threats they may pose to rangeland sustainability, this article focuses on the ecological sustainability of rangelands leaving economic and social aspects of rangeland sustainability beyond the current scope. The reason is twofold: (a) the ecological threat is immediate and emerges in several regions around the globe; and (b) remote sensing is used widely for rangeland ecology and a review of its contribution and benefits is timely.

Ecological sustainability in rangelands depends largely on ecosystem functioning and the impact of herds on ecological processes. Based on Hobbs and Norton (1996), livestock grazing can have four major impacts on critical ecological processes: defoliation of plants, soil trampling, mineral deposition (faecal and urine), and atmospheric gas exchange. However, these impacts may be sustainable at an appropriate grazing intensity. Heitschmidt, Vermeire, and Grings (2004) identified three major threats to ecological processes in rangelands: (a) invasion of noxious species that decrease substantially the attractiveness of a given rangeland due to a reduction in the functioning of biomass as forage material; (b) the conversion of rangelands into other land uses such as residential areas, agricultural fields, and industrial areas; and (c) a significant decrease in productivity due to soil degradation as a result of intensified erosion processes and over-grazing.

In the early days of range management as a discipline, monitoring changes in forage, land cover, and land use relied on the judgement and experience of field experts and less on quantitative methods (Booth and Tueller 2003; West 2003). Given widespread availability of computing and statistical software resources, there is a move towards more quantitative and cost-effective methods for rangeland monitoring and assessment (Donahue 1999). Existing methods for rangeland assessment can be divided into two main groups: traditional field techniques, which are based on actual fieldwork and direct measurements of surface covers, and remote-sensing methodologies, which are based on non-intrusive measurements without (or almost without) actual fieldwork. Remote-sensing methodologies include different approaches to measurement:

(1) panchromatic, coloured, and infrared aerial photography that includes methods of visual interpretation and image tone analysis;
(2) optical data that include the use of vegetation indices and more advanced radiative transfer models; and
(3) radar data that include the use of theoretical and semi-empirical methods.

Remote sensing provides excellent opportunities to observe, monitor, forecast, and ultimately understand the threats to ecological processes in rangelands. Remote sensing has historically been used to provide three forms of information that are of use in rangeland monitoring:

(1) categorical observation (what is there?),
(2) quantitative observation (how much is there?), and
(3) dynamic monitoring (what is going on there?).

The combination of time series remotely sensed imagery with spatially distributed process models furthers this 'monitoring' information set to provide forecasts of future states (what is likely to happen in the future?) and process understanding (what is causing the changes?).

Remote sensing has the advantage of covering large areas with frequent repetitive image acquisition in multiple wavelengths. Application of a wide variety of methodologies to map surface components using these data can allow identification of invasive species, the detection of land-use changes, and early warning of land degradation risks. Indeed until today, a large number of remote-sensing studies have been applied to tackle these challenges. Yet, to the best of our knowledge, the remote-sensing literature has not provided a review that surveys the use of remotely sensed data to study the threats to the ecological sustainability of rangelands.

The *aim* of this study is, therefore, to review the current uses of remote sensing for analysing the major threats to ecological sustainability of rangelands: invasion of noxious plants, conversion to other land uses, soil erosion, and biomass reduction. The review is organized according to the three questions mentioned above: what is there? – namely categorizing land-use data based on structured classification; how much is there? – namely quantification of biophysical processes in rangelands; and what is going on there? – namely quantifying the changes and dynamics in rangeland characteristics. Finally, the article will emphasize the research aspects in which further development is recommended.

2. Remote sensing of categorical states

Identification and mapping of vegetation formations, such as shrubs, dwarf shrubs and herbaceous vegetation, is crucial for understanding ecological processes in rangelands and for better range management. Maps of vegetation formations could lay the basis for managing natural resources in accordance with their carrying capacity. Since the mid-twentieth century, aerial photograph interpretation has been used to produce land resource maps and related reports (e.g. the 1940s pioneer land systems work of Christian and Stewart in Australia). The disadvantage of aerial photographs is their relatively narrow cover and the fact that they comprise relatively poor spectral information. However, in satellite remote sensing, mapping vegetation formations is not a trivial task as the mixture of vegetation formations occupies, in many cases, the sub-pixel domain of most satellite sensor images. That is, vegetation objects or patches may be smaller than a pixel. Furthermore, due to the spectral similarity of most vegetation formations, class separation is difficult. For example, separation of perennial shrubs and annual grasses requires analysis of differences in the length of their growing periods (Geerken et al. 2005) when using the temporal or multitemporal approach. The multitemporal approach uses repeated multispectral measurements acquired throughout the growing season on dates chosen to reflect changes in vegetation phenology (Shoshany and Svoray 2002; Singh and Glenn 2009; Svoray and Karnieli 2011). However, the phenological approach has the disadvantage of requiring the purchase and processing of a large number of images and the requirement for sufficient clear sky images, which can be problematic at certain locations (e.g. the UK) and times (e.g. northern high-latitude winter) when cloud cover is generally high.

Hyperspectral measurements have great potential for mapping vegetation in rangelands due to the large number of narrow spectral bands provided and the unique hyperspectral response of each species. Yang, Everitt, and Johnson (2009), for example, applied the minimum noise fraction transformation and different classification techniques to airborne hyperspectral imagery for mapping Ashe juniper infestations in central Texas. The overall accuracy varied between 84% and 97% using the spectral angle mapper (SAM), maximum likelihood classification (MLC), and Mahalanobis distance classification techniques depending on the approach and site. In another study, Oldeland et al. (2010) used fine spatial resolution hyperspectral data sets to map vegetation units of a semiarid rangeland in Central Namibia. Vegetation and soil spectral indices were calculated from hyperspectral images and used as environmental variables in a constrained ordination by applying redundancy analysis. The resulting statistical relationships between vegetation data and spectral indices were used to create images of ordination axes, which were subsequently used in a supervised fuzzy *c*-means classification approach relying on a *k*-nearest neighbour (*k*-NN) distance metric. Membership images for each vegetation unit as well as a confusion image of the classification result allowed a sound ecological interpretation of the resulting hard classification map.

Table 1 presents several studies conducted between 2000 and 2011 on mapping surface components from different rangelands around the world. The methods applied in these studies vary, but the general classification accuracy, despite different environments, surface characteristics, and climates, is encouraging. Classification accuracy in most cases was $>70\%$, suggesting that remote sensing provides a reliable tool for mapping and archiving surface components in rangelands. This collection of studies also includes widely available satellite sensor images such as Landsat Thematic Mapper (TM) and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER). The use of IKONOS tends to increase classification accuracy mainly due to the fact that vegetation objects or clusters in most rangelands are smaller than the pixel resolution of Landsat. Table 1 shows clearly that different image processing techniques affect the classification accuracy substantially. The study of Lu et al. (2007), which applied different classification techniques to the same set of data, showed that the use of the normalized difference vegetation index (NDVI) substantially increased classification accuracy, while the use of MLC and extraction and classification of homogeneous objects (ECHO) with NDVI produced the most accurate results. From a survey of the literature, the use of Hyperion has not been widespread despite the fact that it provides hyperspectral data from space that can map wide regions. The limited uptake of what appears to be a potentially useful data source may be due to the greater difficulty of handling hyperspectral data.

Table 1. Categorical mapping of surface components in rangelands.

Author	Sensor	Country	Rainfall (mm)	Classified groups	Classification method	Accuracy (%)
Jensen et al. (2001)	Landsat TM	North Dakota	360–410	Habitat type	Discriminant analysis	54–100, depending on vegetation type and climate
Williams and Hunt (2002)	AVIRIS	Wyoming	442	Leafy spurge: prairie sites, wooded sites	Mixture tuned matched filtering	69.9
South, Qi, and Lusch (2004)	Landsat 7	Southern Michigan and northern Indiana	834	Agricultural crops: traditional tillage, no tillage	Mahalanobis classifier (MC)	72.88
					Maximum likelihood	72.88
					Minimum distance	78.82
					Spectral angle mapping (SAM)	96.10
					Cosine angle concept	97.27
Lawrence (2004)	IKONOS	California	1100	Range, tree, water, meadow, rock, grass	CTA	CTA, 84; SGB, 94
	Probe-1	Montana	400		SGB	CTA, 83; SGB, 93
	Landsat ETM+	Yellowstone	550			CTA, 64; SGB, 62
Filippi and Jensen (2006)	AVIRIS	Florida	1200–1500+	Wetlands, grasses shrubs, trees dry/burned vegetation	ANN FLVQ (hyperspectral)	82.82 Normalized accuracy: 74.6
Lu et al. (2007)	AISA	Japan	1530	Agricultural crops, grass, tree, soil	DBFE-MLC	85
					With NDVI	92.4
					DBFE-ECHO	85
					With NDVI	93.3
					PCA-MLC	66.3

(*Continued*)

Table 1. (*Continued*).

Author	Sensor	Country	Rainfall (mm)	Classified groups	Classification method	Accuracy (%)
					With NDVI	72.5
					PCA-ECHO	69.6
					With NDVI	73.8
Wang et al. (2007)	CASI	Italy	820	Salt-marsh vegetation	Neural Network (NN)	84
					Community based NN Classifier	91
Fritz et al. (2008)	MODIS	Russia	420	Agricultural crops grasses	Temporal NDVI/EVI composite	71.2 – hard classification 86.8 – pure pixel sampling
Mingwei et al. (2008)	MODIS	China	620	Maize, cotton	ISODATA	Maize, 71.1; Cotton, 84
Ustin et al. (2009)	AVIRIS	Nevada	149	Biological soil crusts	Maximum likelihood, spectral angle mapper	
Singh and Glenn (2009)	Landsat ETM+	Idaho	Desert	Cheatgrass	Multitemporal spectral unmixing	77
Oldeland et al. (2010)	HyMap	Namibia	250	Dwarf shrub, rocky soil, grass, shrubs, biocrusts	Fuzzy *c*-means classifier (*k*-NN)	Internal validation: 98 External validation: 64
Wang et al. (2010)	Hyperion	China	397	Irrigated land, terrace, sandy land, residential land, waterbody	Geographic image cognition	80
Jones, Coops, and Sharma (2010)	AISA Lidar	Canada	Quasi-Med.	Tree species	Multiclass SVM	72.3
Peña-Barragán et al. (2011)	ASTER	California	200–460	Agricultural crops, trees, meadow	Decision tree	79

Masocha and Skidmore (2011)	ASTER	Zimbabwe	635	Water, bushland, grassland, soil, rock, woodland	ANN	71.1
	DEM (GIS)				Hybrid ANN + expert system	82.9
					Support vector machine classifier (SVMC)	64.2
					Hybrid SVMC + expert system	75.6

Note: ISODATA, iterative self-organizing data analysis technique; DEM, digital elevation model; CTA, classification tree analysis; SGB, stochastic gradient boosting; ANN FLVQ, artificial neural network fuzzy learning vector quantization; DBFE, decision boundary feature extraction; AISA, airborne imaging spectroradiometer for application.

Identification of invasive species from space is an even more complex task than identification of natural vegetation formations, since many invaders occur as mid-level canopy species or as understory and, therefore, contribute little to the spectra captured in remotely sensed images (Masocha and Skidmore 2011). Nevertheless, the effect of invaders and especially noxious invaders on rangelands is substantial and thus justifies the effort. One solution may be the use of unmixing approaches to unravel pixel heterogeneity. For example, the study of Frazier and Wang (2011) suggests a method for discretizing sub-pixel data to generate landscape metrics using a continuum of fractional cover thresholds. The approach developed was used to transform sub-pixel classifications (i.e. maps of land-cover proportions) into discrete maps of salt cedar in the Rio Grande basin. Analysis of metric trends provided evidence that salt cedar had expanded away from the immediate riparian zones and was displacing native vegetation. Another approach that can contribute to overcoming the limitations of the coarse spatial resolution of remotely sensed data is the use of ancillary data. Masocha and Skidmore (2011) used a neural network (NN) and a support vector machine (SVM) to map four cover classes of the invasive shrub *Lantana camara* in Zimbabwe. The remotely sensed data were combined with a geographical information system (GIS)-based expert system to test their contribution to invasive species cover maps. The NN, when used on its own, mapped the cover of *L. camara* with a kappa accuracy of 0.61. When it was combined with an expert system, the kappa value increased to 0.77. Similarly, the SVM achieved a kappa of 0.52, whereas the hybrid expert system achieved a significantly higher kappa of 0.67. These results suggest that integrating conventional image classifiers with an expert system can increase the accuracy of invasive species mapping. Juniper encroachment into shrub steppe and grassland systems is one of the most prominent changes occurring in the rangelands of western North America. Sankey et al. (2010) fused Landsat 5 TM-based and light detection and ranging (lidar)-based classifications to evaluate juniper expansion patterns in Idaho, and this fusion-based juniper classification model performed well (83% overall accuracy). A comparison of the resulting juniper presence/absence map to a 1965 vegetation-cover map indicated 85% juniper expansion, which was consistent with field data. More studies on the use of remotely sensed data to map invasive species in rangelands are provided by Starks et al. (2011) with QuickBird images; Naylor, Endress, and Parks (2005) with the use of coloured aerial photographs; and the review work by Hunt et al. (2003).

Rangelands in dry areas are subject to biological soil crusting including life forms such as cyanobacteria, moss, and lichen. Biogenic crusts exclude herbaceous vegetation and can act as an indicator of the response of ecosystems to disturbances. Ustin et al. (2009) examined the potential for spectral detection of different biological soil crusts using field and airborne spectroscopy and found that hyperspectral imagery could be used to monitor local and perhaps regional changes in biological soil crust in the southwestern deserts of the USA, even if crust components were not detected individually. Other studies to identify biological crusts from remotely sensed data include those of Karnieli (1997) and Karnieli et al. (1996, 1999).

To summarize this 'what is there?' section, we can say that current remote-sensing data and methods allow identification of vegetation formations, with the limitation of pixel resolution and, of more relevance to rangeland sustainability, the identification of species and invasive species, with the use of ancillary data and sophisticated image processing methods.

3. Remote sensing of biophysical quantities

Although other approaches exist (Table 2), this review reveals that the remote sensing of the biophysical properties of vegetation in open areas, and in rangelands in particular, is

Table 2. Estimates of vegetation productivity in rangelands.

Author	Satellite sensor	Country	Rainfall depth (mm)	Vegetation type	Estimation method	Accuracy (%)
Bouman (1991)	Radar (X-band FM-CW)	The Netherlands	630–890	Beet, potato, wheat, barley	Multitemporal, multiangle, and co-polarized radar backscattering	Wheat, 79 Barley, 73
Svoray et al. (2001)	ERS-2	Israel	420	Herbaceous vegetation, shrubs, dwarf shrubs, trees	Indexing	85
Wang et al. (2002)	Landsat TM	China	594	Grass, forest, seablite, reed	Above ground biomass (carbon storage)	
Hansen and Schjoerring (2003)	Dual spectrometer SD2000	Roskilde, Denmark	458	Wheat	PLSR GBM PLSR LAI PLSR Chl_{conc} PLSR $Chl_{density}$ PLSR N_{conc} PLSR $N_{density}$	89 75 30 60 71 71
Svoray and Shoshany (2003)	ERS-2	Israel	420	Grass	Empirical modelling	78
Bella et al. (2004)	SPOT-4 VEGETATION	France	683–1249	Pasture	STICS-Prairie model	
Calvao and Palmeirim (2004)	Landsat TM	Portugal	580	Scrubs	NDVI leave one out procedure	NDVI, 81 TM bands, 87
Bradford, Hicke, and Lauenroth (2005)	NOAA-AVHRR	USA	400–1000	Grasslands, croplands	Carnegie–Ames–Stanford Approach (APAR and LUE)	CASA, 50 CASA with new croplands, 80

(*Continued*)

Table 2. (*Continued*).

Author	Satellite sensor	Country	Rainfall depth (mm)	Vegetation type	Estimation method	Accuracy (%)
Chen et al. (2009)	MMS-1 portable spectrometer	Tibet	560	Grasslands	Narrow-band vegetation indices; original narrow-band reflectance; first derivative reflectance (FDR); band depth index; PLSR	
Fava et al. (2009)	ASD Fieldspec Handheld spectroradiometer. TM AVIRIS	Sardinia	740	Pastures	OLSR GBM (ASD)	72
					OLSR GBM (TM)	31
					OLSR GBM (AVIRIS)	69
					OLSR LAI (ASD)	76
					OLSR LAI (TM)	30
					OLSR LAI (AVIRIS)	75
					OLSR N (ASD)	73
					OLSR N (TM)	30
					OLSR N (AVIRIS)	72
					OLSR N_C (ASD)	60
					N_C (TM)	4.6
					OLSR N_C (AVIRIS)	55
Brinkmann et al. (2011)	Landsat	Arabian Peninsula	312	Grasses, sub-shrubs, forbs	ANPP	77

Note: GBM, green biomass; CASA, Carnegie Ames Stanford Approach; STICS, Simulateur Multidiscplinaire pour les Cultures Standard; PLSR, partial least squares regression; OLSR, ordinary least square linear regression.

conducted in many cases with the help of vegetation indices (e.g. Reeves, Zhao, and Running 2006; Hunt and Miyake 2006; Fang et al. 2005). Among these vegetation indices, the most common is the NDVI. Despite some criticism of NDVI due to its being influenced by noise deriving from soil moisture or being insensitive to subtle variation in vegetation properties, it appears that its use has become almost the norm for estimating biophysical variables. NDVI can serve as an indicator for principal ecosystem features such as productivity and biomass, the fraction of absorbed photosynthetically active radiation intercepted, CO_2 fluxes, and, since the rate of greening can be correlated with food value, vegetation quality for herbivores (Pettorelli et al. 2005). The use of NDVI can also be improved using ancillary data. In heterogeneous semiarid areas, an empirical NDVI-based model was found to be appropriate for biomass estimation, using the ratio between mean annual rainfall and a threshold rain level representing the transition from dwarf shrub to shrub dominance (Shoshany and Karnibad 2011). Among the advantages of NDVI are its ease of use and its fairly robust relationship with biophysical properties (mainly vegetation cover and productivity). Given the recent decrease in the use of field measurements due to limitations of labour and budget (Donahue 1999), it is expected that the use of NDVI as a representative measure of rangeland health and productivity will increase. Nevertheless, future users need to be cautious when using NDVI as it has several drawbacks; for example, the correlation with vegetation cover may be low where vegetation is photosynthetically inert for long periods.

Among the remote-sensing data with potential to quantify biophysical properties in three dimensions are microwave data and, in particular, synthetic aperture radar (SAR) data. The advantages of SAR are that it provides greater canopy penetration depth than optical data, it is sensitive to different properties of the soil and vegetation, and it can penetrate through rain, fog, and night-time conditions. Still, several disadvantages should be mentioned, including the difficulties encountered with radiometrically and geometrically calibrating SAR images and the necessary removal of the speckle effect (Ulaby, Moore, and Fung 1986). Recent work with SAR data in rangelands has been related in many cases to biomass estimation. Table 2 surveys several studies aimed at predicting vegetation productivity in rangelands, among them the SAR-based studies of Svoray et al. (2001) and Svoray and Shoshany (2003).

Some rangelands (e.g. Mediterranean rangelands) provide special challenges for remote-sensing-based vegetation mapping. Being heterogeneous in cover, hilly at times, and with a relatively small area and sparse distribution of biomass vegetation, mapping in the Mediterranean region requires high sensitivity from prediction models. Rangeland mapping in Mediterranean areas requires fine spatial resolution satellite sensor images or, in many cases as a substitute for fine spatial resolution, the use of spectral unmixing modelling. Very large-scale (fine spatial resolution) aerial photograph imagery has been demonstrated to increase the speed and accuracy of ecological monitoring relative to ground surveys (Booth and Cox 2008). Moreover, unmanned aerial vehicles have been used to provide such imagery at fine spatial resolutions for rangeland monitoring purposes and, in particular, the identification of plants to species (Laliberte et al. 2010). Such approaches offer great promise where the spatial frequency of variation in the property of interest demands a fine spatial resolution.

Studies such as those of Svoray and Shoshany (2003) applied the multitemporal unmixing method (Shoshany and Svoray 2002) embedded in a water cloud SAR-based model using Landsat TM images and ERS-2 images to predict herbaceous vegetation biomass, thereby gaining a classification accuracy of 78%. In more recent work, Röder et al. (2008) used Landsat TM and enhanced TM (ETM) images to study the impact of grazing on a rangeland ecosystem in Greece. They showed that temporal trends reflect the underlying pattern of potential livestock distribution at the per-pixel level, with a spatially differentiated pattern of both positive and negative trends in close proximity. Nonetheless, no direct relation was established between vegetation cover and animal stocking rates at the community level. The authors suggested that this aggregation level is too coarse given the combination of highly heterogeneous landscapes and intensive land tenure systems. Within-pixel fractional components of PV (photosynthetic vegetation), NPV (non-photosynthetic vegetation), and bare soil contribute to rangeland management by enhancing climate and land-use control over the functional properties of arid and semiarid ecosystems and, therefore, improving ecological sustainability. Asner and Heidebrecht (2002) compared systematically multispectral and hyperspectral sampling schemes for quantifying PV, NPV, and bare soil cover using spectral mixture models.

Another possible source of remote-sensing data for monitoring rangelands is lidar. However, this technology needs more fine tuning to be fitted to the most common component in rangelands, herbaceous vegetation (Su and Bork 2007). Su and Bork (2007) showed the usability of fine spatial resolution airborne lidar for quantifying biophysical characteristics of multiple community types within rangeland environments in central Alberta, Canada. The authors found the data useful for quantifying height, cover, and density of the overstory vegetation within forest communities. However, the height and cover of shrublands, as well as most of the herbaceous communities, were underestimated. The authors concluded that while lidar is useful for characterizing forest properties, the quantification of individual shrublands and grasslands is of more limited applicability currently.

Quantification of ground cover (i.e. the proportion of ground covered by vegetation) is among the more frequently requested tasks in range management and ecosystem studies. Although more advanced methods and data sources exist, the use of vertical photography for cover analysis is widely reported in the literature (Booth and Tueller 2003), including dedicated software packages developed specifically for this purpose (Richardson, Karcher, and Purcell 2001). Despite some limitations, including the requirement of being physically present in the field, the coverage of only relatively small areas, and the need for a specific tripod or crane, this data source is economically viable, easy to use, and perhaps, most importantly, provides data at a scale of centimetres such that it can resolve vegetation individuals in rangelands – a task not possible by any other data source in remote sensing (Booth and Tueller 2003).

An important measure of rangeland functioning is moisture level in the vegetation canopy, an expression of its physiological status. The complementary measure is the soil moisture content. Long periods of dry soil and low levels of canopy moisture, as well as more readily detectable decreases in leaf area index (LAI), can imply a deteriorating ecosystem due to drought impact. Decreases in LAI and canopy moisture can, therefore, provide important information on the health of plants and on drying processes due to drought years or climatic change. Since plants are expected to dry out slowly before mortality (Claudio et al. 2006), it is useful to monitor LAI and water content in the canopy. This is why several remote-sensing studies used hyperspectral remote sensing for accurate estimation of canopy water content of grasses and grazed fen meadow (e.g. Clevers, Kooistra, and Schaepman 2010). Canopy moisture assessment includes attempts to estimate daily evapotranspiration (ET) fluxes at the catchment scale from National Oceanic and Atmospheric Administration (NOAA)-11 Advanced Very High Resolution Radiometer (AVHRR) satellite sensor data (Kustas et al. 1994) and, more recently, studies that provide robust, yet simple remote-sensing methodologies for mapping instantaneous land-surface fluxes of water, energy, and CO_2 exchanges within a coupled framework (Anderson et al. 2008).

As many of the rangelands on Earth are situated in dry areas, soil moisture is among the most important variables to be monitored using remote-sensing technologies. It is probably the reason why considerable effort has been invested in estimating soil water content in rangelands. Studies of soil moisture in rangelands were applied using optical data mainly with the infrared band and SAR data using theoretical models, but also semi-empirical models (Shoshany et al. 2000; Svoray and Shoshany 2004). Other studies have used passive microwave data to measure soil moisture using, for example, the Soil Moisture and Ocean Salinity (SMOS) radiometer (Albergel et al. 2011). However, given the complex reality of rangelands, direct measurement of soil moisture may not be sufficient. For example, Contreras et al. (2011) introduced an approach to estimate (with relative error in the range 2–18%) the impacts of external water supplies on arid rangelands in Argentina using mean annual precipitation (MAP) and the enhanced vegetation index (EVI) from Moderate Resolution Imaging Spectrometer (MODIS) imagery. These indices allowed quantification of the impact of remote lateral inflows as well as local constraints on the water balance of rangelands, including irrigated fields and natural oases. Other approaches can take advantage of the implications of water–vegetation patterns on biophysical properties. For example, Shoshany (2012) developed a new model that estimates shrub biomass based on pattern parameterization that represents the effect of shrub patches' spatial arrangement on their water use efficiency. Shrubland biomass productivity was then estimated by modulating rainfall availability along climatic gradients by this Pattern Water Use Efficiency.

Foliar chemistry and gas exchange between vegetation and the atmosphere have long been among the more sought after targets in remote sensing (Curran 1989). Phillips, Beeri, and Liebig (2006) used Landsat 5 to estimate canopy C:N ratios with $<14\%$ error and ASTER satellite sensor data on experimental grazing treatments with 9.6% error. Mutanga and Skidmore (2004) suggested an integrated approach, involving continuum removal to detect and quantify two absorption features located in the visible (R550-757) and shortwave infrared (R2015-2199) bands from an atmospherically corrected HYMAP MKI image. NN was applied to the absorption features together with the red edge position to map grass nitrogen concentration in an African savanna rangeland. Their results indicated that the method could explain 60% of the variation in savanna grass nitrogen concentration on an independent test data set. This accuracy is greater than that for multiple linear regression, which yielded an R^2 of 38%. The study demonstrates the potential of airborne hyperspectral data and NN to estimate and ultimately map nitrogen concentration in the mixed-species environments of South Africa. Mutanga, Skidmore, and Prins (2004) investigated the possibility of estimating the concentration of *in situ* biochemicals in a savanna rangeland, using the spectral reflectance of five grass species. The predictions were in close agreement with validation data and, when data were partitioned into species groups, the R^2 values increased significantly to >0.80.

So, the question 'how much is there?' is being actively addressed for rangelands using remote sensing. A large arsenal of data and methodologies is currently available to study vegetation productivity. This includes multispectral and hyperspectral optical data, SAR data, and lidar. A continuous assessment of vegetation productivity in regard to other attributes can help to assess rangeland status and dynamics between deterioration and recovery and to maintain sustainable grazing pressures.

4. Remote sensing of change

Surface processes, whether human- or animal-driven, biotic, or physical, are inherently dynamic in time and space. Moreover, the prevailing paradigm in modern range management is the State and Transition Model proposed by Westoby, Walker, and Noy-Meir (1989), which emphasizes the structural and compositional changes in rangeland vegetation. Briske, Fuhlendorf, and Smeins (2003) stressed the importance of monitoring large-scale (landscape) spatial changes for effective rangeland evaluation. It is necessary, therefore, to be able to monitor changes in rangelands, especially those prone to large disturbances such as drought, intensive erosion, or colonization by humans, animals, or plants (Palmer and Fortescue 2004; Rietkerk et al. 1996). A monitoring system designed to detect change actually has a fourfold task. It should (a) identify a 'change' when it occurs; (b) declare a 'no change' when a change does not occur; (c) avoid identification of 'no change' when a change occurs; and (d) avoid identification of 'change' when a change does not occur.

Geoff Pickup, an Australian scientist, was one of the first to introduce remote-sensing-based techniques to range management evaluation. He and his colleagues defined a set of range condition indicators that could be measured and monitored by satellites (Pickup, Bastin, and Chewings 1994). A model was developed which exploited the spatial and temporal variation detected in remotely sensed imagery to discriminate between natural climate and anthropogenic influences on degradation (Pickup, Bastin, and Chewings 1994, 1998). More specifically, distance from watering points was used as a surrogate for herd density, allowing Pickup and Chewings (1994) to develop a vegetation-cover index that corresponded to the degradation level along gradients.

Among the most commonly studied changes in rangelands are land-cover (mainly vegetation-cover) and land-use changes. Land-use/land-cover (LULC) change detection using remotely sensed images has been widely applied for environmental monitoring with local and global consequences (Foley et al. 2005). For example, Mucher et al. (2000) investigated the applicability of multispectral and multitemporal satellite sensor data for Pan-European Land Cover Monitoring using a 1 km spatial resolution pan-European land-cover database that was updated using NOAA-AVHRR satellite sensor data. The methodology was found potentially useful for land-cover mapping, but with limitations in monitoring changes due to the coarse spatial resolution of the AVHRR-derived land-cover data. Change detection based on the use of thematic (e.g. vegetation) proportion images is generally preferable as it has the potential to overcome the limitation of a coarse spatial resolution, highlighting areas where the proportions of various land-cover types have changed.

Monitoring within-class changes in amounts (e.g. proportional cover, biomass) can be more difficult than changes in land cover, especially where inter-annual variation is of interest and, thus, where large changes in moisture availability may affect the outcome (Washington-Allen et al. 2006). Serneels, Said, and Lambin. (2001) studied vegetation-cover changes over more than a decade in Kenya's rangelands using NDVI-based change detection techniques applied to AVHRR and Landsat TM images. The data sources were found to be complementary: AVHRR was found to be useful for detecting areas that are sensitive to inter-annual climate fluctuations, but are not subjected to land-cover conversion, while Landsat data allowed the detection of land-cover conversions between consecutive dates that have a more permanent character and are independent of climate-induced fluctuations in surface attributes. Table 3 lists a collection of studies on LULC monitoring applied to rangelands around the world including the Middle East, Europe, Africa, the Far East, and Australia. Satellite sensor data are available from the 1970s, thus allowing analysis of time series of up to 40 years, a period that can be meaningful from the ecological point of view. Indeed, the entire Landsat archive has been made freely available (Woodcock et al. 2008), providing complete coverage of the whole globe every 16 days

Table 3. Land-use and land-cover change in rangelands.

Author	Satellite sensor	Country	Rainfall (mm)	Vegetation type	Process	Period
Mucher et al. (2000)	NOAA-AVHRR (for update the system)	Europe (with The Netherlands as a case study)	700	Grassland, urban, forest, agriculture	Land-use/land-cover change	1995
Serneels, Said, and Lambin (2001)	NOAA-AVHRR	Kenya	400	Savannah vegetation	Land-cover changes	1981–1994
Weiss, Marsh, and Pfirman (2001)	NOAA-AVHRR	Saudi Arabia	100	Rangelands	Vegetative biomass change (COV of NDVI)	1982–1994
Serra, Pons and Sauri (2003)	Landsat TM Landsat MSS	Spain	602	Agricultural crops, meadows and pastures, herbaceous, urban	LCLU change detection	1970s and 1990s
Le Hégarat-Mascle, Ottlé, and Guérin (2005)	NOAA/AVHRR, SPOT/VGT-S10, SPOT/VGT-P	France	990	fields to grassland, afforestation–reforestation–deforestation	Iterative estimation and previous state information	1980–2000
Zhong and Wang (2006)	Lansat ETM	China	589	Saline soils	Independence component analysis	1995, 2002
Bontemps et al. (2008)	CBERS-1 SPOT-VEGETATION	Rondônia	1750–2000	Tropical forest	Object-based method	2001, 2004
Im, Jensen, and Tullis (2008)	QuickBird	Las Vegas, USA	110	Urban area	Object/neighbourhood correlation image analysis and image segmentation techniques	2002–2003

(*Continued*)

Table 3. (*Continued*).

Author	Satellite sensor	Country	Rainfall (mm)	Vegetation type	Process	Period
Zhou, Li, and Kurban (2008)	Landsat MSS, TM, ETM; SPOT HRV	China	150	Cropland, grassland, woodland	Temporal trajectory analysis	1973–2000
Berberoglu and Akin (2009)	Landsat TM	Turkey	647	Agriculture, woodland, wetland vegetation, sand dune vegetation	Image differencing, image rationing, image regression, change vector analysis (CVA)	1985–2005
Verbesselt et al. (2010)	MODIS	Australia	1072	Forest, grassland	BFAST algorithm	2000–2009
Boulila et al. (2011)	SPOT 5	Reunion Island	5000	Non-dense vegetation, forest	Fuzzy sets and data mining	2004, 2006

at a spatial resolution of 30 m (previously 80 m for the multispectral scanning system (MSS)) since 1972. The spatial resolution of remotely sensed imagery varies from a few metres to a few kilometres, although most temporal analyses are undertaken using coarse-resolution images such as from the NOAA-AVHRR and Système Pour l'Observation de la Terre (SPOT) VEGETATION sensors. The reasons for this predominance are mainly the fine temporal resolution that these satellite sensors provide (daily data), but also the low (or zero) cost and the fact that remote sensing is used in many cases to study regional and even global phenomena.

Changes in dry rangelands have been investigated quite extensively, most probably due to their vulnerability to drought and to increased use of extensive agriculture. Yool, Makaio, and Watts (1997) used Landsat MSS images to detect rangeland changes in southern New Mexico, where extensive grasslands have gradually become a patchwork of shrublands and relict grasslands. The data were evaluated for changes using the following: (a) differences between the red bands of July 1983 and August 1992 scenes; (b) the Euclidean distances between the red and infrared bands for the two scenes; and (c) a principal component analysis (PCA) using all eight MSS bands. Correlation coefficients among these images ranged from 0.83 to 0.95.

The study of change can contribute to our understanding of rangeland dynamics in time, but also in place. For example, Wallace et al. (2003) used temporal satellite sensor data to quantify LULC change and to relate spatial configuration and composition to landscape structure and pattern. The findings indicated that conversion of a fire-suppressed native grassland area has two spatial components: in the rural areas, grass is excluded by increasingly expanding shrub and mesquite-dominated cover, whereas in the urban and suburban areas, grass as well as shrubs and mesquite are eliminated by a fragmented and expanding urban landscape. In another study from this part of the world (Arizona and Sonora, Mexico), Kepner et al. (2000) developed a simple procedure to document changes and determine ecosystem vulnerabilities through the use of change detection and indicator development regarding traditional degradation processes. The authors developed landscape metrics as sensitive measures of change due to human or natural disturbances. This project utilized data from the North American Landscape Characterization (NALC) project, which incorporates triplicate Landsat MSS imagery from the early 1970s, mid-1980s, and 1990s. Observed changes in land cover during the study period indicated that extensive, highly connected grassland and desert scrub areas were the most vulnerable ecosystems to fragmentation and actual loss due to encroachment of xerophytic mesquite woodland.

Bennouna et al. (2004) established a multitemporal methodology for monitoring and detecting changes in arid rangelands using the red and near-infrared (NIR) bands. This approach included visual interpretation of SPOT images to describe the distribution of vegetative biomass in the study area. Radiometric analysis (monitoring the correlation coefficient between the red and NIR bands) was then used to reveal the dynamic of each vegetation formation. The rate of vegetation development was correlated with climatic and socio-economic data to determine its principal causes. Finally, the changes occurring in each vegetation formation were mapped according to the NIR/red ratio. In Morocco, Chikhaoui et al. (2005) studied soil erosion, landslides, deforestation, and human pressure. The land degradation index developed in this study using ASTER data yielded 85% accuracy in mapping land degradation. Other studies that assessed rangeland degradation using multitemporal satellite sensor images include: Paudel and Andersen (2010) in the Upper Mustang, Trans Himalaya, Nepal; Brinkmann et al. (2011) in the Arabian Peninsula; Munyati and Makgale (2009) in South Africa; and Hostert et al. (2003) in Greece.

In addition, human intervention and land-use changes can have a dramatic effect on the ecology of a rangeland environment. Karnieli et al. (2008) studied soil and vegetation degradation around watering points in the Central Asian dry rangelands using the Tasseled Cap brightness index to enhance the contrast between areas close to wells and the darker surrounding areas. Semivariograms were estimated to characterize the spatial structure present in the space-borne imagery of two desert sites and in three key time periods (mid-to-late 1970s, around 1990, and 2000). The Kriging interpolation technique was applied to smooth the brightness index values extracted from images of 30–80 m spatial resolution to assess spatial and temporal land-cover patterns. Change detection analysis, based on the Kriging prediction maps, was performed to assess the direction and intensity of changes between the study periods. The authors found that degradation occurred in some areas due to recent exploration and exploitation of gas and oil reserves in the region. Another area was subject to rehabilitation of the rangeland due to a dramatic decrease in the number of livestock – an outcome of socio-economic changes accompanying the independence of Kazakhstan in 1991.

5. Coupling remote sensing with process models

An important development has been the use of spatially and temporally explicit modelling coupled with remotely sensed data. Coupled modelling approaches can be used to understand soil, water, and ecological processes and also to forecast the future response of rangelands to changing conditions. Pickup and Chewings (1988) proposed to integrate Landsat MSS data and a cattle distribution model to calculate actual grazing intensity and trampling in large paddocks. The idea of merging remote sensing with GIS-based spatial models emerged during the early days of the two disciplines, but became common during the 1990s (Fraser, Warren, and Barten 1995). The potential benefits of the coupled approach to the study of rangelands are obvious, given that understanding of surface processes is sought. Svoray et al. (2004) developed a physically based model based on GIS, remote sensing, and fuzzy logic to assess habitat productivity in a basaltic stony Mediterranean rangeland. Four indirect variables representing major characteristics of herbaceous habitats were used as model input: rock cover fraction, topographic wetness index, soil depth, and slope aspect. A linear unmixing model was used to measure rock cover on a per-pixel basis using a Landsat TM summer image. The model rules were based on fuzzy logic and were formulated based on the hypothesized water requirements of the herbaceous vegetation. Several scenarios involving changes in slope aspect and rockiness were tested. Herbaceous biomass measurements at two time intervals (mid and peak winter season) corresponded most closely with habitat assessment predictions based on a new scenario that suggested that rockiness increases herbaceous production on south-facing slopes, while on other slopes rock cover has a lower impact on herbaceous growth. Such process-based approaches are more likely to be generalizable to other regions than models formulated on a purely empirical basis. Svoray et al. (2008) extended the model to be temporally dynamic (daily iterations).

In another application involving computer simulation, Milner-Gulland et al. (2006) used a multi-agent-based model (ABM) to examine trade-offs in the allocation of wealth between capital and flocks in Kazakhstan. Model predictions matched field observations and it was found that seasonal migratory herds had a good opportunity to re-establish when distant pastures provided limited winter forage. Another model that has been coupled with remotely sensed data is the cellular automata (CA). CA are most commonly applied on regular grids, which make remotely sensed imagery an ideal source of input data. Grid cell values are updated at each iteration of the model, based on the application of a set of simple rules to a local neighbourhood around the central cell. He et al. (2005) presented a CA-based method to support local government efforts to zone grassland protected areas in Xilingol steppe in the Inner Mongolia Autonomous Region of China. The authors integrated a CA model with GIS and remote-sensing data to extract candidate protected areas and to simulate the zoning of these areas. The authors showed that the proposed method of grassland protection zoning provided valuable decision support tools for decision-makers and planners.

Physically based process models have also been applied to rangelands. Ben Wu, Redeker, and Thurow (2001) developed a set of woody cover ET regression curves for different range sites based on simulation studies using the SPUR-91 hydrologic model. Based on these regression curves and GIS analysis, the authors found that a 'no brush' management policy would result in a 35% decrease in water yield, while a hypothetical brush management cost-share programme would increase water yield by 43%. Benefits in water yield and forage production from brush management differed across range sites. A brush management cost-share programme that preferentially allocated brush management to sites with deep soil and the highest forage production potential increased water yield by 50%, compared with a 100% increase when brush management was preferentially allocated to sites with shallow soil and the highest water yield potential. de Jong et al. (1999) used the Soil Erosion Model for Mediterranean (SEMMED) regions to produce regional maps of simulated soil loss for two Mediterranean test sites. The model demonstrated the integrated use of multitemporal Landsat TM images to account for vegetation properties and a digital terrain model to account for topographical properties, and to assess the transport capacity of overland flow. In addition, a digital soil map and field data were used to assess the spatial distribution of soil properties. SEMMED was found to be most sensitive to the initial soil moisture storage capacity and soil detachability index, but it was able to simulate processes at a regional scale.

6. Discussion

The focus of future studies of rangelands is likely to be on monitoring critical (e.g. indicator) properties of ecosystems over time. Specifically, attention will likely focus on monitoring ecosystem sustainability in the face of the threats posed by noxious invasive species, LULC conversion, and land degradation due to soil erosion and over-grazing (Heitschmidt, Vermeire, and Grings 2004) as well as increased drought, fire, and climate change generally. All of these threats are amenable to monitoring through remote sensing, as the survey of the literature above demonstrates. At a coarse spatial resolution (e.g. 1 km), vast areas of rangelands can be monitored with a high temporal frequency (e.g. daily) using imagery such as that from MODIS. At this spatial resolution, monitoring is likely to focus on vegetation cover and vegetation phenology as well as a range of geomorphological and hydrological variables such as soil moisture, as discussed above. Vegetation phenology, in particular, is of great interest as phenology is (a) affected by, and sensitive to, external drivers such as climate, hydrological, and anthropogenic changes and (b) affects land–atmosphere interactions such as carbon exchange and energy fluxes. Inter-annual changes in phenological parameters, such as the start and end of seasons, can be used as indicators of stresses on ecosystems such as those from invasive plants or soil degradation. Although many methods for estimating phenological parameters from space are now readily available (e.g. Dash, Jeganathan, and Atkinson 2010; Jeganathan, Dash, and Atkinson 2010), application to rangelands is likely to be hampered by the sparse distribution and percentage cover of rangeland vegetation and so it is recommended that research be focused on addressing this problem.

Equally, all of the above threats are amenable to process modelling, given suitable parameterizations of the models and suitable remote-sensing data to provide boundary conditions and updates. We argue that the coupling of remotely sensed data with process models is likely to grow in importance as a mechanism for simulating rangeland ecosystem processes and functioning, and for evaluating likely future outcomes in the face of threats to sustainability. At a coarse spatial resolution, the invasion of noxious species, LULC conversion, and soil erosion are all amenable to the application of simple process models such as CA (Engelen et al. 1995; Balzter, Braun, and Kohler 1998; Batty 2007). While the understanding process generated by such simple models is limited, dynamic processes such as dispersion of invading plant species or conversion of LULC can be simulated allowing sensitivity analysis, evaluation of what-if scenarios and a limited amount of forecasting (Dunkerly 1997; He et al. 2005). Examples of these types of models are now common, as applied to rangeland productivity (Svoray et al. 2008), land degradation, and soil erosion (de Jong et al. 1999) and rangeland hydrology (Ben Wu, Redeker, and Thurow 2001).

At a fine spatial scale, process models such as ABMs that are more representative of human and animal behaviours can also be applied usefully to rangelands (e.g. Milner-Gulland et al. 2006, as discussed above). ABMs can also be applied to model the movements of livestock (Dumont and Hill 2001). As they move around while grazing, animals' interactions with vegetation and the soil (soil erosion caused by trampling) can be modelled explicitly, providing a feedback into other models. Such approaches may be beneficial in understanding how changing spatial patterns and densities of livestock, and grazing behaviours, over time (e.g. diurnal, seasonal) lead to unsustainable over-grazing pressure. The combination of multiple modelling approaches with remote-sensing data is most likely to yield the greatest insights – specifically, where human–landscape and animal–landscape interactions are modelled explicitly (Engelen et al. 1995). At a fine spatial scale, the coupling of spatially distributed hydrological, geomorphological, and vegetation growth models driven by fine spatial resolution remote-sensing data, with agent-based models of human decision-making and animal movements, is likely to provide a beneficial framework within which to evaluate what-if scenarios (e.g. climate change scenarios), provide short-term forecasts, and provide greater understanding for the ultimate benefit of rangeland management.

7. Summary

Based on a review of the remote sensing of rangelands presented above, the following conclusions can be drawn.

(1) Classification of vegetation formations in rangelands is possible with reasonable accuracy from multispectral imagery. However, multitemporal data often provide increased accuracy by exploiting class-specific vegetation phenological changes. More research is required on methods for exploiting hyperspectral data, which can be expensive and for which it is often hard to achieve a time series of clear sky images (e.g. in high northern latitudes).
(2) Invasive species, while one of the three major threats identified by Heitschmidt, Vermeire, and Grings (2004), present a challenge for mapping and more research is recommended focusing on fusion between remotely sensed data and ancillary data employing expert systems.

(3) Biophysical properties and foliar chemistry have been investigated in many cases using NDVI. Although more modern vegetation indices (e.g. EVI) are available, for rangelands with relatively low biomass and a sparse distribution of herbaceous vegetation, optical data, and NDVI appear to be sufficient in many cases.
(4) The low biomass, sparse distribution, and low height of vegetation in most rangelands limit the applicability of remote-sensing techniques such as microwave and lidar. In view of the increase in the availability of high-spatial resolution images in these wavelengths, more research is required to determine what information can, and cannot, be estimated from rangelands by these technologies.
(5) Land cover and land use provide perhaps the most obvious application of remote-sensing monitoring in rangelands. Since classification and vegetative cover proportion estimates are relatively accurate using most remote-sensing approaches, the detection and temporal analysis of vegetation change are relatively well established. The future direction of monitoring using remote sensing should be the formalization of scenarios of change and estimation of threats under varying conditions.
(6) Studies of changes in rangelands due to accelerated erosion could potentially use lidar data, which have been useful in estimating erosion rates in other scenarios.

Acknowledgements

The roots of this article are in the rangelands sessions organized by TS and AP in the Agri-Sensing International Symposium on Sensing in Agriculture held on 21–24 February 2011 in Haifa, Israel. The authors acknowledge Prof. Paul Curran, who originally coined the phrases ‘what is there?’, ‘how much is there?’, and ‘what is going on there?’ The authors thank Prof. Maxim Shoshany, who encouraged us to write this article, and Lotan Talshir for his help with the literature survey. We thank two anonymous reviewers for their useful comments.

References

Albergel, C., E. Zakharova, J. C. Calvet, M. Zribi, M. Parde, J. P. Wigneron, N. Novello, Y. Kerr, A. Mialon, and N. E. D. Fritz. 2011. “A First Assessment of the SMOS Data in Southwestern France Using in situ and Airborne Soil Moisture Estimates: The CAROLS Airborne Campaign.” *Remote Sensing of Environment* 115: 2718–2728.

Anderson, M. C., J. M. W. Norman, P. Kustas, R. Houborg, P. Starks, J., and N. Agam. 2008. “A Thermal-Based Remote Sensing Technique for Routine Mapping of Land-Surface Carbon, Water and Energy Fluxes from Field to Regional Scales.” *Remote Sensing of Environment* 112: 4227–4241.

Asner, G. P., and K. B. Heidebrecht. 2002. “Spectral Unmixing of Vegetation, Soil and Dry Carbon Cover in Arid Regions: Comparing Multispectral and Hyperspectral Observations.” *International Journal of Remote Sensing* 23: 3939–3958.

Balzter, H., P. W. Braun, and W. Kohler. 1998. “Cellular Automata Models for Vegetation Dynamics.” *Ecological Modelling* 107: 113–125.

Batty, M. 2007. *Cities and Complexity: Understanding Cities with Cellular Automata, Agent-Based Models, and Fractals*. Cambridge, MA: MIT Press.

Bella, D., R. Faivre, F. Ruget, B. Seguin, M. Guerif, B. Combal, M. Weiss, and C. Rebella. 2004. “Remote Sensing Capabilities to Estimate Pasture Production in France.” *International Journal of Remote Sensing* 25: 5359–5372.

Ben Wu, X., E. J. Redeker, and T. L. Thurow. 2001. “Vegetation and Water Yield Dynamics in an Edwards Plateau Watershed.” *Journal of Range Management* 54: 98–105.

Bennouna, T., A. Nejmeddine, M. J. Lefevre-Fonollosa, J. P. Lacombe, M. Kaemmerer, and J. C. Revel. 2004. “Detection of Change in Moroccan Rangelands with Multitemporal Spot Imagery.” *Arid Land Research and Management* 18: 229–240.

Berberoglu, S., and A. Akin. 2009. "Assessing Different Remote Sensing Techniques to Detect Land Use/Cover Changes in the Eastern Mediterranean." *International Journal of Applied Earth Observation and Geoinformation* 11: 46–53.
Bontemps, S., P. Bogaert, N. Titeux, and P. Defourny. 2008. "An Object-Based Change Detection Method Accounting for Temporal Dependences in Time Series with Medium to Coarse Spatial Resolution." *Remote Sensing of Environment* 112: 3181–3191.
Booth, D. T., and S. E. Cox. 2008. "Image-Based Monitoring to Measure Ecological Change in Rangeland." *Frontiers in Ecology* 6: 185–190.
Booth, D. T., and P. T. Tueller. 2003. "Rangeland Monitoring Using Remote Sensing." *Arid Land Research and Management* 17: 455–467.
Boulila, W., I. R. Farah, K. S. Ettabaa, B. Solaiman, and H. B. Ghézala. 2011. "A Data Mining Based Approach to Predict Spatiotemporal Changes in Satellite Images." *International Journal of Applied Earth Observation and Geoinformation* 13: 386–395.
Bouman, B. A. M. 1991. "Crop Parameter-Estimation from Ground-Based X-Band (3-cm Wave) Radar Backscattering Data." *Remote Sensing of Environment* 37: 193–205.
Bradford, J. B., J. A. Hicke, and W. K. Lauenroth. 2005. "The Relative Importance of Light-Use Efficiency Modifications from Environmental Conditions and Cultivation for Estimation of Large-Scale Net Primary Productivity." *Remote Sensing of Environment* 96: 246–255.
Brinkmann, K., U. Dickhoefer, E. Schlecht, and A. Buerkert. 2011. "Quantification of Aboveground Rangeland Productivity and Anthropogenic Degradation on the Arabian Peninsula Using Landsat Imagery and Field Inventory Data." *Remote Sensing of Environment* 115: 465–474.
Briske, D. D., S. D. Fuhlendorf, and F. E. Smeins. 2003. "Vegetation Dynamics on Rangelands: A Critique of the Current Paradigms." *Journal of Applied Ecology* 40: 601–614.
Calvao, T., and J. M. Palmeirim. 2004. "Mapping Mediterranean Scrub with Satellite Imagery: Biomass Estimation and Spectral Behavior." *International Journal of Remote Sensing* 25: 3113–3126.
Chen, J., S. Gu, M. Shen, Y. Tang, and B. Matsushita. 2009. "Estimating Aboveground Biomass of Grassland Having a High Canopy Cover: An Exploratory Analysis of In Situ Hyperspectral Data." *International Journal of Remote Sensing* 30: 6497–6517.
Chikhaoui, M., F. Bonn, A. Bokoye, and A. Merzouk. 2005. "A Spectral Index for Land Degradation Mapping Using ASTER Data: Application to a Semi-arid Mediterranean Catchment." *International Journal of Applied Earth Observation and Geoinformation* 7: 140–153.
Claudio, H. C., Y. Cheng, D. A. Fuentes, J. A. Gamon, H. Luo, W. Oechel, H. L. Qiu, A. F. Rahman, and D. A. Sims. 2006. "Monitoring Drought Effects on Vegetation Water Content and Fluxes in Chaparral with the 970 nm Water Band Index." *Remote Sensing of Environment* 103: 304–311.
Clevers, J. G. P. W., L. Kooistra, and M. E. Schaepman. 2010. "Estimating Canopy Water Content Using Hyperspectral Remote Sensing Data." *International Journal of Applied Earth Observation and Geoinformation* 12: 119–125.
Contreras, S., E. G. Jobbagy, P. E. Villagra, M. D. Nosetto, and J. Puigdefabregas. 2011. "Remote Sensing Estimates of Supplementary Water Consumption by Arid Ecosystems of Central Argentina." *Journal of Hydrology* 397: 10–22.
Curran, P. J. 1989. "Remote Sensing of Foliar Chemistry." *Remote Sensing of Environment* 30: 271–278.
Dash, J., C. Jeganathan, and P. M. Atkinson. 2010. "Satellite Sensor Derived Spatio-Temporal Variation in Vegetation Phenology over India." *Remote Sensing of Environment* 114: 1388–1402.
de Jong, S. M., M. L. Paracchini, F. Bertolo, S. Folving, J. Megier, and A. P. J. de Roo. 1999. "Regional Assessment of Soil Erosion Using the Distributed Model SEMMED and Remotely Sensed Data." *Catena* 37: 291–308.
Donahue, D. L. 1999. *The Western Range Revisited: Removing Livestock from Public Range to Conserve Native Biodiversity*. Norman: University of Oklahoma Press.
Dumont, B., and D. R. C. Hill. 2001. "Multi-Agent Simulation of Group Foraging in Sheep: Effects of Spatial Memory, Conspecific Attraction and Plot Size." *Ecological Modelling* 141: 201–215.
Dunkerly, D. L. 1997. "Banded Vegetation: Development Under Uniform Rainfall from a Simple Cellular Automaton Model." *Plant Ecology* 129: 103–111.
Engelen, G., R. White, I. Uljee, and P. Drazan. 1995. "Using Cellular Automata for Integrated Modelling of Socio-Environmental Systems." *Environmental Monitoring and Assessment* 34: 203–214.
Fang, H. L., S. L. Liang, M. P. McClaran, W. J. D. van Leeuwen, S. Drake, S. E. Marsh, A. M. Thomson, R. C. Izaurralde, and N. J. Rosenberg. 2005. "Biophysical Characterization and

Management Effects on Semiarid Rangeland Observed from Landsat ETM Plus Data." *IEEE Transactions on Geoscience and Remote Sensing* 43: 125–134.
Fava, F., R. Colombo, S. Bocchi, M. Meroni, M. Sitzia, N. Fois, and C. Zucca. 2009. "Identification of Hyperspectral Vegetation Indices for Mediterranean Pasture Characterization." *International Journal of Applied Earth Observation and Geoinformation* 11: 233–243.
Filippi, A. M., and J. R. Jensen. 2006. "Fuzzy Learning Vector Quantization for Hyperspectral Coastal Vegetation Classification." *Remote Sensing of Environment* 100: 512–530.
Flather, C. H., and C. H. Sieg. 2000. "Applicability of Montreal Process Criterion 1 – Conservation of Biological Diversity – To Rangeland Sustainability." *International Journal of Sustainable Development & World Ecology* 7: 81–96.
Foley, J. A., R. DeFries, G. P. Asner, C. Barford, G. Bonan, S. R. Carpenter, F. S. Chapin, M. T. Coe, G. C. Daily, H. K. Gibbs, J. H. Helkowski, T. Holloway, E. A. Howard, C. J. Kucharik, C. Monfreda, J. A. Patz, I. C. Prentice, N. Ramankutty, P. K. Snyder. 2005. "Global Consequences of Land Use." *Science* 309: 570–574.
Fraser, R. H., M. V. Warren, and P. K. Barten. 1995. "Comparative-Evaluation of Land-Cover Data Sources for Erosion Prediction." *Water Resources Bulletin* 31: 991–1000.
Frazier, A. E., and L. Wang. 2011. "Characterizing Spatial Patterns of Invasive Species Using Sub-Pixel Classifications." *Remote Sensing of Environment* 115: 1997–2007.
Fritz, S., M. Massart, I. Savin, J. Gallego, and F. Rembold. 2008. "The Use of MODIS Data to Derive Acreage Estimations for Larger Fields: A Case Study in the South-Western Rostov Region of Russia." *International Journal of Applied Earth Observation and Geoinformation* 10: 453–466.
Geerken, R., N. Batikha, D. Celis, and E. Depauw. 2005. "Differentiation of Rangeland Vegetation and Assessment of Its Status: Field Investigations and MODIS and SPOT VEGETATION Data Analyses." *International Journal of Remote Sensing* 26: 4499–4526.
Ginguld, M., A. Perevolotsky, and E. D. Ungar. 1997. "Living on the Margins: Livelihood Strategies of Bedouin Herd-Owners in the Northern Negev, Israel." *Human Ecology* 25: 567–591.
Hansen, P. M., and J. K. Schjoerring. 2003. "Reflectance Measurement of Canopy Biomass and Nitrogen Status in Wheat Crops Using Normalized Difference Vegetation Indices and Partial Least Squares Regression." *Remote Sensing of Environment* 86: 542–553.
He, C., Q. Zhang, Y. Li, X. Li, and P. Shi. 2005. "Zoning Grassland Protection Area Using Remote Sensing and Cellular Automata Modelling – A Case Study in Xilingol Steppe Grassland in Northern China." *Journal of Arid Environments* 63: 814–826.
Heady, H. F., and R. D. Child. 1994. *Rangeland Ecology & Management*. Boulder, CO: Westview Press
Heitschmidt, R. K., L. T. Vermeire, and E. E. Grings. 2004. "Is Rangeland Agriculture Sustainable?." *Journal of Animal Science* 82: E138–E146.
Hobbs, R. J., and D. A. Norton. 1996. "Towards a Conceptual Framework for Restoration Ecology." *Restoration Ecology* 4: 93–110.
Hostert, P., A. Roder, J. Hill, T. Udelhoven, and G. Tsiourlis. 2003. "Retrospective Studies of Grazing-Induced Land Degradation: A Case Study in Central Crete, Greece." *International Journal of Remote Sensing* 24: 4019–4034.
Huenneke, L. F., J. P. Anderson, M. Remmenga, and W. H. Schlesinger. 2002. "Desertification Alters Patterns of Aboveground Net Primary Production in Chihuahuan Ecosystems." *Global Change Biology* 8: 247–264.
Hunt, E. R., J. H. Everitt, J. C. Ritchie, M. S. Moran, D. T. Booth, G. L. Anderson, P. E. Clark, and M. S. Seyfried. 2003. "Applications and Research Using Remote Sensing for Rangeland Management." *Photogrammetric Engineering and Remote Sensing* 69: 675–693.
Hunt, E. R. Jr., and B. A. Miyake. 2006. "Comparison of Stocking Rates from Remote Sensing and Geospatial Data." *Rangeland Ecology & Management* 59: 11–18.
Im, J., J. R. Jensen, and J. A. Tullis. 2008. "Object-Based Change Detection Using Correlation Image Analysis and Image Segmentation." *International Journal of Remote Sensing* 29: 399–423.
Jeganathan, C., J. Dash, and P. M. Atkinson. 2010. "Characterising the Spatial Pattern of Phenology for the Tropical Vegetation of India Using Multi-Temporal MERIS Chlorophyll Data." *Landscape Ecology* 25: 1125–1141.
Jensen, M. E., J. P. Dibenedetto, J. A. Barber, C. Montagne, and P. S. Bourgeron. 2001. "Spatial Modeling of Rangeland Potential Vegetation Environments." *Journal of Range Management* 54: 528–536.

Jones, T. G., N. C. Coops, and T. Sharma. 2010. “Assessing the Utility of Airborne Hyperspectral and LiDAR Data for Species Distribution Mapping in the Coastal Pacific Northwest, Canada.” *Remote Sensing of Environment* 114: 2841–2852.

Kustas, W. P., E. M. Perry, P. C. Doraiswamy, and M. S. Moran. 1994. “Using Satellite Remote Sensing to Extrapolate Evapotranspiration Estimates in Time and Space over a Semiarid Rangeland Basin.” *Remote Sensing of Environment* 49: 275–286.

Laliberte, A. S., J. E. Herrick, A. Rango, and C. Winters. 2010. “Acquisition, Orthorectification, and Object-Based Classification of Unmanned Aerial Vehicle (UAV) Imagery for Rangeland Monitoring.” *Photogrammetric Engineering and Remote Sensing* 76: 661–672.

Lawrence, R. 2004. “Classification of Remotely Sensed Imagery Using Stochastic Gradient Boosting as a Refinement of Classification Tree Analysis.” *Remote Sensing of Environment* 90: 331–336.

Le Hégarat-Mascle, S., C. Ottlé, and C. Guérin. 2005. “Land Cover Change Detection at Coarse Spatial Scales Based on Iterative Estimation and Previous State Information.” *Remote Sensing of Environment* 95: 464–479.

Lu, S., K. Oki, Y. Shimizu, and K. Omasa. 2007. “Comparison Between Several Feature Extraction/Classification Methods for Mapping Complicated Agricultural Land Use Patches Using Airborne Hyperspectral Data.” *International Journal of Remote Sensing* 28: 963–984.

Karnieli, A. 1997. “Development and Implementation of Spectral Crust Index over Dune Sands.” *International Journal of Remote Sensing* 18: 1207–1220.

Karnieli, A., U. Gilad, M. Ponzet, T. Svoray, R. Mirzadinov, and O. Fedorina. 2008. “Assessing Land-Cover Change and Degradation in the Central Asian Deserts Using Satellite Image Processing and Geostatistical Methods.” *Journal of Arid Environments* 72: 2093–2105.

Karnieli, A., G. J. Kidron, C. Glaesser, and E. Ben-Dor. 1999. “Spectral Characteristics of Cyanobacteria Soil Crust in Semiarid Environments.” *Remote Sensing of Environment* 69: 67–75.

Karnieli, A., M. Shackak, H. Tsoar, E. Zaady, Y. Kaufman, A. Danin, and W. Porter. 1996. “The Effect of Microphytes on the Spectral Reflectance of Vegetation in Semiarid Regions.” *Remote Sensing of Environment* 57: 88–96.

Kepner, W. G., C. J. Watts, C. M. Edmonds, J. K. Maingi, S. E. Marsh, and G. Luna. 2000. “Landscape Approach for Detecting and Evaluating Change in a Semiarid Environment.” *Environmental Monitoring and Assessment* 64: 179–195.

Maczko, K. A., L. D. Bryant, Thompson, D. W., and S. J. Borchard. 2004. “Putting the Pieces Together: Assessing Social, Ecological, and Economic Rangeland Sustainability.” *Rangelands* 26: 3–14.

Masocha, M., and A. K. Skidmore. 2011. “Integrating Conventional Classifiers with a GIS Expert System to Increase the Accuracy of Invasive Species Mapping. *International Journal of Applied Earth Observation and Geoinformation* 13: 487–494.

Milner-Gulland, E. J., C. Kerven, R. Behnke, I. A. Wright, and A. Smailov. 2006. “A Multi-Agent System Model of Pastoralist Behaviour in Kazakhstan.” *Ecological Complexity* 3: 23–36.

Mingwei, Z., Z. Qingbo, C. Zhongxin, L. Jia, Z. Yong, and C. Chongfa. 2008. “Crop Discrimination in Northern China with Double Cropping Systems Using Fourier Analysis of Time-Series MODIS Data. *International Journal of Applied Earth Observation and Geoinformation* 10: 476–485.

Mucher, C. A., K. T. Steinnocher, F. P. Kressler, and C. Heunks. 2000. “Land Cover Characterization and Change Detection for Environmental Monitoring of Pan-Europe.” *International Journal of Remote Sensing* 21: 1159–1181.

Munyati, C., and D. Makgale. 2009. “Multitemporal Landsat TM Imagery Analysis for Mapping and Quantifying Degraded Rangeland in the Bahurutshe Communal Grazing Lands, South Africa.” *International Journal of Remote Sensing* 30: 3649–3668.

Mutanga, O., and A. K. Skidmore. 2004. “Integrating Imaging Spectroscopy and Neural Networks to Map Grass Quality in the Kruger National Park, South Africa.” *Remote Sensing of Environment* 90: 104–115.

Mutanga, O., A. K. Skidmore, and H. H. T. Prins. 2004. “Predicting In Situ Pasture Quality in the Kruger National Park, South Africa, Using Continuum-Removed Absorption Features.” *Remote Sensing of Environment* 89: 393–408.

Naylor, B. J., B. A. Endress, and C. G. Parks. 2005. “Multiscale Detection of Sulfur Cinquefoil Using Aerial Photography.” *Rangeland Ecology & Management* 58: 447–451.

Oldeland, J., W. Dorigo, L. Lieckfeld, A. Lucieer, and N. Jürgens. 2010. “Combining Vegetation Indices, Constrained Ordination and Fuzzy Classification for Mapping Semi-Natural Vegetation Units from Hyperspectral Imagery.” *Remote Sensing of Environment* 114: 1155–1166.

Palmer, A. R., and A. Fortescue. 2004. "Remote Sensing and Change Detection in Rangelands." *African Journal of Range & Forage Science* 21: 123–128.

Paudel, K. P., and P. Andersen. 2010. "Assessing Rangeland Degradation Using Multi-Temporal Satellite Images and Grazing Pressure Surface Model in Upper Mustang, Trans Himalaya, Nepal." *Remote Sensing of Environment* 114: 1845–1855.

Peña-Barragán, J. M., M. K. Ngugi, R. E. Plant, and J. Six. 2011. "Object-Based Crop Identification Using Multiple Vegetation Indices, Textural Features and Crop Phenology." *Remote Sensing of Environment* 115: 1301–1316.

Pettorelli, N., J. O. Vik, A. Mysterud, J. M. Gaillard, C. J. Tucker, and N. C. Stenseth. 2005. "Using the Satellite-Derived NDVI to Assess Ecological Responses to Environmental Change." *Trends in Ecology & Evolution* 20: 503–510.

Phillips, R. L., O. Beeri, and M. Liebig. 2006. "Landscape Estimation of Canopy C:N Ratios Under Variable Drought Stress in Northern Great Plains Rangelands." *Journal of Geophysical Research-Biogeosciences* 111: G2.

Pickup, G., G. N. Bastin, and V. H. Chewings. 1994. "Remote-Sensing-Based Condition Assessment for Nonequilibrium Rangelands Under Large-Scale Commercial Grazing." *Ecological Applications* 4: 497–517.

Pickup, G., G. N. Bastin, and V. H. Chewings. 1998. "Identifying Trends in Land Degradation in Non-equilibrium Rangelands." *Journal of Applied Ecology* 35, 365–377.

Pickup, G., and V. H. Chewings. 1988. "Estimating the Distribution of Grazing and Patterns of Cattle Movement in a Large Arid Zone Paddock an Approach Using Animal Distribution Models and Landsat Imagery." *International Journal of Remote Sensing* 9: 1469–1490.

Pickup, G., and V. H. Chewings. 1994. "A Grazing Gradient Approach to Land Degradation Assessment in Arid Areas from Remotely-Sensed Data. *International Journal of Remote Sensing* 15: 597–617.

Reeves, M. C., M. Zhao, and S. W. Running. 2006. "Applying Improved Estimates of MODIS Productivity to Characterize Grassland Vegetation Dynamics." *Rangeland Ecology & Management* 59: 1–10.

Richardson, M. D., D. E. Karcher, and L. C. Purcell. 2001. "Quantifying Turfgrass Cover Using Digital Image Analysis." *Crop Science* 41: 1884–1888.

Rietkerk, M., P. Ketner, L. Stroosnijder, and H. H. T., Prins. 1996. "Sahelian Rangeland Development: A Catastrophe?." *Journal of Range Management* 49: 512–519.

Röder, A., T. Udelhoven, J. Hill, G. del Barrio, and G. Tsiourlis. 2008. "Trend Analysis of Landsat-TM and -ETM+ Imagery to Monitor Grazing Impact in a Rangeland Ecosystem in Northern Greece." *Remote Sensing of Environment* 112: 2863–2875.

Sankey, T. T., N. Glenn, S. Ehinger, A. Boehm, and S. Hardegree. 2010. "Characterizing Western Juniper Expansion via a Fusion of Landsat 5 Thematic Mapper and Lidar Data." *Rangeland Ecology & Management* 63: 514–523.

Serneels, S., M. Y. Said, and E. F. Lambin. 2001. "Land Cover Changes Around a Major East African Wildlife Reserve: The Mara Ecosystem (Kenya)." *International Journal of Remote Sensing* 22: 3397–3420.

Serra, P., X. Pons, and D. Sauri. 2003. "Post-Classification Change Detection with Data from Different Sensors: Some Accuracy Considerations." *International Journal of Remote Sensing* 24: 3311–3340.

Shoshany, M. 2012. "The Rational Model of Shrubland Biomass, Pattern and Precipitation Relationships along Semiarid Climatic Gradients." *Journal of Arid Environments* 78: 179–182.

Shoshany, M., and N. Goldshleger. 2002. "Land-Use and Population Density Changes in Israel – 1950 to 1990: Analysis of Regional and Local Trends." *Land Use Policy* 19: 123–133.

Shoshany, M., and L. Karnibad. 2011. "Mapping Shrubland Biomass along Mediterranean Climatic Gradients: The Synergy of Rainfall-Based and NDVI Based Models." *International Journal of Remote Sensing* 32: 9497–9508.

Shoshany, M., and T. Svoray. 2002. "Multidate Adaptive Unmixing and Its Application to Analysis of Ecosystem Transitions along a Climatic Gradient." *Remote Sensing of Environment* 82: 5–20.

Shoshany, M., T. Svoray, P. J. Curran, G. M. Foody, and A. Perevolotsky. 2000. "The Relationship Between ERS-2 SAR Backscatter and Soil Moisture: Generalization from a Humid to Semi-Arid Transect." *International Journal of Remote Sensing* 21: 2337–2343.

Singh, N., and N. F. Glenn. 2009. "Multitemporal Spectral Analysis for Cheatgrass (Bromus tectorum) Classification." *International Journal of Remote Sensing* 30: 3441–3462.

South, S., J. Qi, and D. P. Lusch. 2004. “Optimal Classification Methods for Mapping Agricultural Tillage Practices.” *Remote Sensing of Environment* 91: 90–97.

Starks, P. J., B. C. Venuto, J. A. Eckroat, and T. Lucas. 2011. “Measuring Eastern Redcedar (Juniperus virginiana L.) Mass with the Use of Satellite Imagery.” *Rangeland Ecology & Management* 64: 178–186.

Su, J. G., and E. W. Bork. 2007. “Characterization of Diverse Plant Communities in Aspen Parkland Rangeland Using LiDAR Data.” *Applied Vegetation Science* 10: 407–416.

Svoray, T., S. B. Y. Gancharski, Z. Henkin, and M. Gutman. 2004. “Assessment of Herbaceous Plant Habitats in Water-Constrained Environments: Predicting Indirect Effects with Fuzzy Logic.” *Ecological Modelling* 180: 537–556.

Svoray, T., and A. Karnieli. 2011. “Rainfall, Topography, and Primary Production Relationships in a Semiarid Ecosystem.” *Ecohydrology* 4: 56–66.

Svoray, T., R. Shafran-Nathan, Z. Henkin, and A. Perevolotsky. 2008. “Spatially and Temporally Explicit Modeling of Conditions for Primary Production of Annuals in Dry Environments.” *Ecological Modelling* 218: 339–353.

Svoray, T., and M. Shoshany. 2003. “Herbaceous Biomass Retrieval in Habitats of Complex Composition: A Model Merging SAR Images with Unmixed Landsat TM Data.” *IEEE Transactions on Geoscience and Remote Sensing* 41: 1592–1601.

Svoray, T., and M. Shoshany. 2004. “Multi-Scale Analysis of Intrinsic Soil Factors from SAR-Based Mapping of Drying Rates.” *Remote Sensing of Environment* 92: 233–246.

Svoray, T., M. Shoshany, P. J. Curran, G. M. Foody, and A. Perevolotsky. 2001. “Relationship Between Green Leaf Biomass Volumetric Density and ERS-2 SAR Backscatter of Four Vegetation Formations in the Semi-Arid Zone of Israel.” *International Journal of Remote Sensing* 22: 1601–1607.

Ulaby, F. T., M. K. Moore, and A. K. Fung. 1986. *Microwave Remote Sensing Active and Passive: from Theory to Applications*. Norwood, MA: Artech House.

Ustin, S. L., P. G. Valko, S. C. Kefauver, M. J. Santos, J. F. Zimpfer, and S. D. Smith. 2009. “Remote Sensing of Biological Soil Crust Under Simulated Climate Change Manipulations in the Mojave Desert.” *Remote Sensing of Environment* 113: 317–328.

Verbesselt, J., R. Hyndman, A. Zeileis, and D. Culvenor. 2010. “Phenological Change Detection While Accounting for Abrupt and Gradual Trends in Satellite Image Time Series.” *Remote Sensing of Environment* 114: 2970–2980.

Wallace, O. C., J. G. Qi, P. Heilma, and R. C. Marsett. 2003. “Remote Sensing for Cover Change Assessment in Southeast Arizona.” *Journal of Range Management* 56: 402–409.

Wang, C., M. Menenti, M.-P. Stoll, E. Belluco, and M. Marani. 2007. “Mapping Mixed Vegetation Communities in Salt Marshes Using Airborne Spectral Data.” *Remote Sensing of Environment* 107: 559–570.

Wang, J., Y. Chen, T. He, C. Lv, and A. Liu. 2010. “Application of Geographic Image Cognition Approach in Land Type Classification Using Hyperion Image: A Case Study in China.” *International Journal of Applied Earth Observation and Geoinformation* 12: S212–S222.

Wang, S. Q., J. Xu, C. H. Zhou, and C. F. He. 2002. “Using Remote Sensing to Estimate the Change of Carbon Storage: A Case Study in the Estuary of Yellow River Delta.” *International Journal of Remote Sensing* 23: 1565–1580.

Washington-Allen, R. A., N. E. West, R. D. Ramsey, and R. A. Efroymson. 2006. “A Protocol for Retrospective Remote Sensing-Based Ecological Monitoring of Rangelands.” *Rangeland Ecology & Management* 59: 19–29.

Weiss, E., S. E. Marsh, and E. S. Pfirman. 2001. “Application of NOAA-AVHRR NDVI Time-Series Data to Assess Changes in Saudi Arabia’s Rangelands.” *International Journal of Remote Sensing* 22: 1005–1027.

West, N. E. 2003. “Theoretical Underpinnings of Rangeland Monitoring.” *Arid Land Research and Management* 17: 333–346.

Westoby, M., B. Walker, and I. Noy-Meir. 1989. “Opportunistic Management for Rangelands Not at Equilibrium.” *Journal of Range Management* 42: 266–274.

Williams, A. P., and E. R. Hunt. 2002. “Estimation of Leafy Spurge Cover from Hyperspectral Imagery Using Mixture Tuned Matched Filtering.” *Remote Sensing of Environment* 82: 446–456.

Woodcock, C. E., R. G. Allen, M. Anderson, A. Belward, R. Bindschadler, W. B. Cohen, F. Gao, S. N. Goward, D. L. Helder, E. H. Helmer, R. Nemani, L. Oreopoulos, J. R. Schott, P. S. Thenkabail, E. F. Vermote, J. E. Vogelmann, M. A. Wulder, and R. Wynne. 2008. “Free Access to Landsat Imagery.” *Science* 320: 1011.

Yang, C. H., J. H. Everitt, and H. B. Johnson. 2009. "Applying Image Transformation and Classification Techniques to Airborne Hyperspectral Imagery for Mapping Ashe Juniper Infestations." *International Journal of Remote Sensing* 30: 2741–2758.

Yool, S. R., M. J. Makaio, and J. M. Watts. 1997. "Techniques for Computer-Assisted Mapping of Rangeland Change." *Journal of Range Management* 50: 307–314.

Zhong, J., and R. Wang. 2006. "Multi-Temporal Remote Sensing Change Detection Based on Independent Component Analysis. *International Journal of Remote Sensing* 27: 2055–2061.

Zhou, Q., B. Li, and A. Kurban. 2008. "Trajectory Analysis of Land Cover Change in Arid Environment of China." *International Journal of Remote Sensing* 29: 1093–1107.