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Remote sensing for conservation monitoring: Assessing protected areas, habitat extent, habitat condition, species diversity, and threats

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ABSTRACT

Monitoring protected areas and their surrounds at local to regional scales is essential given their vulnerability to anthropogenic pressures, including those associated with climatic fluctuation, and important for management and fulfilment of national and international directives and agreements. Whilst monitoring has commonly revolved around field data, remote sensing can play a key role in establishing baselines of the extent and condition of habitats and associated species diversity as well as quantifying losses, degradation or recovery associated with specific events or processes. Landsat images constitute a major data source for habitat monitoring, capturing broad scale information on changes in habitat extent and spatial patterns of fragmentation that allow disturbances in protected areas to be identified. These data are, however, less able to provide information on changes in habitat quality, species distribution and fine-scale disturbances, and hence data from other spaceborne optical sensors are increasingly being considered. Very High Resolution (VHR) optical datasets have been exploited to a lesser extent, partly because of the relative recency of spaceborne observations and challenges associated with obtaining and routinely extracting information from airborne multi-spectral and hyperspectral datasets. The lack of a shortwave infrared band in many VHR datasets and provision of too much detail (e.g., shadows within and from landscape objects) also present challenges in some cases. Light Detection and Ranging (LiDAR) and Synthetic Aperture Radar (SAR) data, particularly when used synergistically with optical data, have benefited the detection of changes in the three-dimensional structure of habitats. This review shows that remote sensing has a strong, yet underexploited potential to assist in the monitoring of protected areas. However, the data generated need to be utilized more effectively to enable better management of the condition of protected areas and their surrounds, prepare for climate change, and assist planning for future landscape management.

1. Introduction

In an era of increasing human pressure on ecosystems and biodiversity, protected areas have emerged as a cornerstone of efforts towards conservation (Nelson and Chomitz, 2011). There are currently close to 133,000 protected areas worldwide, covering over 12% of the surface area of terrestrial biomes, which represents an increase of 400% since the 1970s (Butchart et al., 2010). Conservation agencies and governments routinely use information on the number of protected areas, the area under protection and expenditure on conservation to demonstrate commitment to and the impact of conservation measures. For instance, the Convention on Biological Diversity (CBD) endorses and has used protected area coverage as an indicator for testing progress towards its target of reducing the rate of biodiversity loss by 2010 (Chape et al., 2005; Butchart et al., 2010). A similar approach was followed by the European Union to measure progress towards the ambitious goal of halting biodiversity loss (Pereira and Cooper, 2006; EEA, 2009).

Protected areas can range from "paper parks" that do not exist on the ground, to extremely effective conservation areas with innovative, inclusive and adaptive programs for sustainable management

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(Timko and Innes, 2009). Consequently, whilst the area that is protected is an indicator of conservation inputs, this measure does not provide an assessment of conservation effectiveness in terms of habitat protection, preservation of biodiversity and/or prevention of habitat fragmentation (Nagendra, 2008; Nelson and Chomitz, 2011). There is therefore a real need for developing more focused targets, including aiming for improvements in habitat condition within protected areas (Mace et al., 2010). Information on progress towards or away from these targets is essential to evaluate the effectiveness of protected area establishment and management, and to put in place adaptive measures to address emerging challenges such as climate change. Monitoring of habitat patches located outside protected areas, which may serve as important connecting elements of protected areas networks (e.g., corridors or "stepping stones"), is also critical when assessing biodiversity conservation success within protected areas (DeFries et al., 2005; Mücher et al., 2009). Such monitoring (including within the protected areas) is needed to evaluate functional links between focal places under protection and their context (including threats), which define the "effective area" (Wiens, 2009) of such places. Finally habitat, protected area and effective area monitoring by means of remote sensing is an important component of the comprehensive monitoring advocated by Wiens et al. (2011) which requires the detection of signals of changes in the distribution and abundance of species.

A number of global databases, notably those developed by the World Database on Protected Areas (WDPA) as well as other efforts by the International Union for Conservation of Nature (IUCN), European Commission – Joint Research Centre (EC-JRC), World Wide Fund for Nature (WWF) and National Aeronautics and Space Administration USA (NASA), have attempted to provide improved assessments of conservation progress by providing global spatial data on protected area coverage, biodiversity and land cover. While useful for making international assessments at regional and global scales, these datasets may suffer from spatial inaccuracies and lack sufficient spatial and thematic detail for local governments, managers or communities to use for effective monitoring of single protected areas (Chape et al., 2005; Gillespie et al., 2008) or even regional park networks (Pereira and Cooper, 2006). Regional to global land cover products from satellite sensors such as the Landsat Thematic Mapper (TM), SPOT (Système Pour l'Observation de la Terre) High Resolution Geometric (HRG) and Terra-1 Moderate Resolution Imaging Spectroradiometer (MODIS) are becoming more widely available. However, there are often discrepancies between these different products, as well as between maps generated at the local scale (DeFries et al., 2005; Nelson and Chomitz, 2011).

An adaptive management approach is needed to buffer political, strategic, tactical and operational uncertainties over how best to manage processes such as natural and human-induced vegetation dynamics for biodiversity conservation. Consideration also needs to be given to the uncertainties posed by climate changes (Lawer et al., 2010). Adaptive management (Holling, 1978; Nyberg, 1998) is a systematic process of enquiry that relies on observations of the impact of human interventions to acquire knowledge on the system observed and then applies this knowledge to improve management practices in a continuous cycle. The system requires the production of fine scale local datasets to generate targeted maps (Mayaux et al., 2005; Fuller, 2005) and inferences on ecosystem functioning. These are of use in at least three different phases of adaptive management, namely problem assessment, monitoring and evaluation of the management practices implemented. As examples, adaptive management has been used in conjunction with remote sensing studies to improve management in private ranges in California, evaluate park networks in Spain (Alcaraz-Segura et al., 2009), and set conservation priorities and monitor conservation effectiveness in US forests (Wiens et al., 2009).

Moderate to high resolution sensors, such as those on board the Landsat and SPOT satellites, provide opportunities for rapid detection of habitat clearing and degradation, particularly as the multi-year and seasonal data provided are free or relatively inexpensive and provide capacity to detect changes over several decades (Hansen et al., 2008; Eva et al., 2010). Since the start of this century, a number of Very High Resolution (VHR) commercial satellites have provided new opportunities for habitat mapping at a finer spatial scale and with a greater thematic resolution and accuracy than previously possible (Nagendra and Rocchini, 2008; Hamel and Andréfouët, 2010). The wider application of these instruments for protected area monitoring was initially limited because of their cost and difficulties in acquiring images for certain locations, but these products are now beginning to be widely used for ecological monitoring (Nagendra and Rocchini, 2008). Hyperspectral imagery, with data on surface radiation measured from a large number of narrow bands, has also improved opportunities for habitat mapping and condition assessment (e.g., by increasing the accuracy of measurement of functionally relevant variables such as the Leaf Area Index (LAI)), which can then be related to important vegetation habitat properties including biomass and forest age (Boyd and Danson, 2005).

Cloud cover and haze creates challenges for monitoring using optical remote sensing, but active remote sensing is largely unaffected by atmospheric conditions. As a result, instruments such as the Synthetic Aperture Radar (SAR) are increasingly being used, with a number of new satellites (e.g., TerraSAR/Tandem-X; Gillespie et al., 2008) providing significant opportunities for landscape monitoring at finer spatial resolution. Although influenced by atmospheric conditions, active Light Detection and Ranging (LiDAR) also allows more targeted assessment and monitoring of landscapes. In particular, both SAR and LiDAR have proved useful for retrieving above ground biomass and also the structure (e.g., height, cover) of woody vegetation, with these relating to forest condition and disturbance regimes. However, their use has been somewhat limited so far because of the technological challenges associated with their use and interpretation (Hyyppä et al., 2000; Boyd and Danson, 2005).

In summary, a wide range of remote sensing data sources (e.g., hyperspatial, hyperspectral and active) and products (e.g., vegetation indices such as the Normalized Difference Vegetation Index (NDVI) and Foliage Projected Cover (FPC)) are beginning to be used for ecological monitoring in a variety of research projects and programs, although their utilization by protected area managers continues to be limited. Several satellite sensors (e.g., those on board the Landsat, Indian Remote Sensing Satellite (IRS) and SPOT satellites) have been providing temporal datasets for several decades. However, significant opportunities are being presented with the increased availability of VHR, hyperspectral, SAR and LiDAR data. However, these data have yet to be used routinely and operationally by many charged with conservation of protected areas, including their surrounds. The following sections of this paper therefore discuss local, regional and global requirements for ecological monitoring and evaluate and convey the utility of different remote sensing platforms for assessing habitat change and degradation, monitoring biodiversity and identifying impacts and pressures.

The paper draws on the experiences of the European Union's Seventh Framework Programme (EU-FP7) project Biodiversity Multi-SOurce Monitoring System: From Space To Species (BIO_SOS, GA 263435), that aims to develop tools and models for consistent multi-annual monitoring of protected areas and their surroundings in the Mediterranean, Northern Europe and other regions including Brazil and India, with these sites located within different climate zones of the world.

2. Local, regional and global requirements for protected area monitoring

Despite the growing awareness of the utility of remote sensing for protected area monitoring, few managers are able to use unprocessed remote sensing data because of the lack of technical skills within management teams and the time-intensive nature of data processing (McDermid et al., 2005; Gross et al., 2009). As an example, a survey of 23 experts from the Bavarian State Forest Administration indicated that the majority considered local forest inventories to be useful for the management of nature conservation areas but they would prefer to work with processed spatial datasets generated routinely for use (Felbermeier et al., 2010). Vanden Borre et al. (2011a) found that although a majority of member states of the EU Habitats Directive (Council Directive 92/43/EEC of 21 May 1992) indicated they had used remote sensing data to assess habitat area and conservation status, they largely relied on subjective and time consuming visual interpretation and were limited by technical expertise.

At the continental scale, the European Union has adopted two directives that are of particular importance for biodiversity conservation – the Council Directive 79/409/EEC of 2 April 1979 on the conservation of wild birds (the Birds Directive: codified as 2009/147/EC); and the Habitats Directive (Schmeller, 2008). The Habitats Directive requires EU member states to conserve rare and/or threatened habitats and species of "community interest" listed in annexes to the Directive. Articles 11 and 17 of the Directive also require member states to report on four parameters of habitat conservation status every six years: habitat area, range, indicators of habitat quality, and future prospects for habitat survival in the member state (European Commission, 2005; Vanden Borre et al., 2011a). A study by Lengyel et al. (2008) of 148 habitat monitoring initiatives across Europe found that the majority of the programs were launched to comply with EU Directives, thus underlining their importance in European assessments of habitat change. Yet, at present, the member states are only able to produce robust trend figures on the range of about 1.7% of habitat types and for no more than 4% of the populations of species listed. Most countries did not produce trend figures at all (European Topic Centre Biodiversity, 2008).

Remote sensing datasets are increasingly being considered by EU member states to satisfy their reporting obligations under the Habitats Directive (Lengyel et al., 2008; Vanden Borre et al., 2011b). For instance, an approach proposed by Jongman et al. (2006) is based on environmental stratification along with detailed field surveys in selected sites, with this utilising remote sensing data in conjunction with GIS databases and modelling. Remote sensing data are also being used by other countries across the world to satisfy their conservation reporting requirements. In Canada, a Parliamentary amendment to the Canada National Parks Act obliges the government to prioritize the maintenance or restoration of ecological integrity while considering park management. The Parks Canada Agency is entrusted with the task of meeting this obligation by preparing a report on park status and ecological integrity for every Canadian park at five year intervals (Fraser et al., 2009). In the USA, the National Parks Service conducts a Vegetation Mapping Program in collaboration with the United States Geological Service (USGS) that uses remote sensing data to map the vegetation of over 270 national parks across the USA (Wang et al., 2009b).

At a global scale, the 10th meeting of the Conference of the Parties (COP), held in Nagoya in October 2010, adopted a revised and updated Strategic Plan for Biodiversity for 2011–2020. Strategic Goal B seeks to "Reduce the direct pressures on biodiversity and promote sustainable use". As part of this goal, protected area managers need to pay special attention to Target 5, "By 2020, the rate of loss of all natural habitats, including forests, is at least halved and where feasible brought close to zero, and degradation and fragmentation is significantly reduced", and to Target 9, "By 2020, invasive alien species and pathways are identified and prioritized, priority species are controlled or eradicated, and measures are in place to manage pathways to prevent their introduction and establishment." Strategic Goal C seeks to "Improve the status of biodiversity by safeguarding ecosystems, species, and genetic diversity". Target 12, a sub-component of Goal C, is particularly relevant for conservation, "By 2020 the extinction of known threatened species has been prevented and their conservation status, particularly of those most in decline, has been improved and sustained." Remote sensing data can play a prominent role in providing information on habitat change, degradation and fragmentation as well as on the spread of invasive species, thereby allowing progress towards meeting these Targets to be monitored (Muchoney and Williams, 2010). However, remote sensing should be used in conjunction with in situ information. The Group on Earth Observations Biodiversity Observation Network (GEO BON), which is recognized by the Parties to the Convention on Biological Diversity and coordinates activities to organize and improve terrestrial, freshwater and marine biodiversity observations globally, has proposed in its observation capabilities report for the CBD to determine Essential Biodiversity variables (EBV) that can be used comparably to and in conjunction with the Essential Climate Variables (GEO BON, 2011). While selecting specific remote sensing datasets, it is critical to keep these goals in mind, as the types of habitats and their correlation with land cover maps can influence the choice of sensors used (McDermid et al., 2005). In particular, to advance towards meeting Target 5, the spatial, spectral and temporal resolution of datasets should enable the assessment of changes in habitat loss, degradation and fragmentation. To progress towards meeting Targets 9 and 12, remote sensing datasets can be used in conjunction with modelling and field information to predict changes in specific species of interest, including endangered and invasive species (e.g. Asner and Martin, 2009; He et al., 2011).

In conclusion, local, regional and global monitoring requirements indicate that monitoring for biodiversity conservation should include four critical areas of assessment – changes in habitat extent and landscape structure, habitat degradation, alterations in biodiversity, and tracking of pressures and threats within and outside protected areas. Consideration also needs to be given to "climate space" shift scenarios (Wiens et al., 2011). Accurate and timely information in these four areas will greatly facilitate informed, active adaptive management by allowing to modify management strategies based on information about their impacts, thereby allowing for more effective conservation. Remote sensing can play a key role, particularly when coupled with field data (Nagendra, 2001). For instance, Nagendra et al. (2010b) use remote sensing in conjunction with field datasets on biodiversity distributions in different management zones in a tiger reserve in India to evaluate the impact of different types of human pressure and management strategies aimed at combatting such pressure. Such approaches hold great promise for adaptive conservation management, requiring the integration of remote sensing analyses with field datasets across different institutional regimes and management gradients, thereby allowing impacts on land cover and habitat change (Nagendra et al., 2008) or fragmentation (Mairota et al., 2012) to be explored. While remote sensing offers great potential for the statistical upscaling of data for regional assessments, downscaling of such datasets to provide local information of use to protected area managers has so far largely been limited by the availability of high quality field information relevant to the scales of observation (Feld et al., 2010). However, the advent of VHR imagery may provide a new and alternative approach to gather information on within habitat heterogeneity (e.g., in terms of condition, structure and species composition).

3. Remote sensing to monitor protected areas

3.1. Habitat mapping and change detection

While the vast majority of remote sensing studies focus on the mapping and delineation of land cover categories, habitat mapping is much harder to undertake although a rule-based approach for generating a national scale habitat map for Wales has just been developed (Lucas et al., 2011). The correspondence between land cover and habitat is far from straightforward. Direct attribution of spectral signatures to habitats requires a great deal of field information (for calibration and validation) and interpretation by experts, with this complicated further by ontological difficulties in relating land cover and habitat classification schemes (McDermid et al., 2005; Lucas et al., 2007; Haest et al., 2010; Tomaselli et al., 2011). Habitat change detection is further complicated by differences in the physical environment and also by the phenological behaviour of plant species comprising habitats, with images acquired ideally from the same season for change detection and from several periods during a year such that discrimination of habitats is optimised. A high level of geometric accuracy between images is also important to avoid erroneous detection of change (Jensen, 2005; Kennedy et al., 2009). A time correspondence between image acquisitions and field campaigns is also desirable for developing and validating classification schemes.

Habitat mapping has hitherto largely been addressed through mapping of one or a few dominant species in the upper canopy (Nagendra, 2001) or by establishing links with their broader biophysical characteristics (e.g., seasonal differences in the relative amounts of photosynthetic and/or non-photosynthetic components; Lucas et al., 2011). Mapping in less complex habitat mosaics is relatively straightforward (Lucas et al., 2007; Lengyel et al., 2008) but is far more challenging where landscapes are more heterogeneous and fine-grained and variation between habitats is more continuous (Varela et al., 2008; Lucas et al., 2011). The structure and complexity of landscapes also often differs between the protected areas and their surrounds and different approaches to mapping often need to be considered.

Some of these issues can be addressed by developing innovative approaches to automated classification including rule-based classification, fuzzy classification, object oriented methods and the use of possibility theory (Bock et al., 2005; Förster and Kleinschmit, 2008; Comber et al., 2010; Haest et al., 2010; Lucas et al., 2011; Kosmidou et al., 2011). Yet fundamentally, the choice of remote sensing datasets will determine the amount of information that is actually available to map complex, fine scale and structurally and floristically variable habitats to sufficient degrees of accuracy and to monitor changes over time. Issues of scale are most critical in the selection of datasets for habitat mapping and the adequacy/quality of spatial datasets and data sources (i.e. their fitness for use, Devillers et al., 2007)) is an important consideration. Perhaps the most obvious and most discussed aspect, certainly the one that comes to the mind of most users of remote sensing data, is that of spatial scale which is comprised of two major components – extent and grain (Kotliar and Wiens, 1990; Forman, 1995). *Extent* refers to the spatial size of the study area under consideration. While the boundary of interest can, in theory, be extended to encompass a very large area, most managers and end-users in practice will be interested in a relatively small buffer around this area, which is generally defined according to opportunistic criteria and does not necessarily bear any functional relation to processes occurring between the protected area and its context. *Grain* refers to the size of the smallest unit for which pixel information is available and is the aspect of spatial scale that is most commonly discussed when selecting data. Although there has been extensive discussion for decades on the need to match the spatial scale to the type of objects (e.g. habitats, species) of focal interest, there is a broad assumption in the ecological community that higher spatial resolution is better and, in general, there is a preference for ordering VHR (small pixel size) data whenever costs permit and data coverage is available (Nagendra and Rocchini, 2008). However, it is also important to note that the spatial grain and extent required depends on the spatial scale of distribution and the heterogeneity of the species and habitats being monitored, the factors that impact species distributions, and the availability of ancillary datasets relating to, for example, soils, drainage networks, geology, topography, population and/or management regimes, that provide additional insights required for interpretation of remote sensing datasets (Nagendra, 2001). As an example, Costanza et al. (2011) found different types of relationships between landscape heterogeneity (measured using the Normalised Difference Vegetation Index (NDVI) as a measure of productivity) and plant species richness as a function of land cover at four different scales.

Whilst the use of VHR data is preferred, there are trade-offs in increasing the spatial resolution to levels that are much finer than the scale of the objects (such as trees, species assemblages or habitats) being studied. For example, shadows caused by objects in the landscape (e.g., buildings, tree canopies) can decrease accuracies in their classification (Fuller, 2005; Nagendra et al., 2010a,b), although suitable image analysis procedures such as segmentation and separate classification of shadow regions using rule-based approaches or spectral unmixing can improve the accuracy of this process (Sawaya et al., 2003; Förster and Kleinschmit, 2008; Haest et al., 2010; Mucher and Kooistra, 2011). Other research has nevertheless demonstrated the benefits of VHR QuickBird imagery for mapping successional fine-scale habitats such as bogs (Bock et al., 2005) and of VHR (<1 m) colour aerial photographs for mapping ecotones and mosaic areas in a landscape in Wales containing complex, fine scale mixture of acid grassland, scattered bracken and acid flushes (Comber et al., 2010).

In many cases, the use of high to moderate (~10–30 m) spatial resolution data, such as provided by the Landsat and the Indian Remote Sensing Satellite (IRS) may be sufficient to capture the broad extent and spatial patterns of habitats (Lucas et al., 2007, 2011). In a complex mountain landscape in the NW Iberian coast, Varela et al. (2008) used Landsat Thematic Mapper imagery with a Digital Elevation Model (DEM) and aerial photographs for a hierarchical habitat classification into 15 classes. However, whilst land cover types such as *Eucalyptus* plantations were easily discerned, different types of heathland and complex agricultural mosaics were more challenging to separate because of the limitations associated with the low spatial and spectral resolution of Landsat TM imagery. An assessment of recent landscape change in mountainous areas of Northern Portugal (Pôças et al., 2011a), also based on Landsat TM imagery, identified a decrease of crop areas and a strong increase of meadows, which the authors related to both demographic and political changes.

Ideally, the size of the pixel should be matched so that it is one quarter to one third of the size of the smallest patches of habitat, species assemblage or individual plant/tree being mapped (Nagendra, 2001). In practice, cost issues often constitute a limitation to mapping, as VHR data from the QuickBird, IKONOS, GeoEye and WorldView-2 sensors tend to be much more expensive compared to HR imagery from SPOT, IRS and Landsat (with the latter now available free of charge). Given that any area will be a heterogeneous mix of objects of different sizes, a multi-scaled analysis using different image datasets may be useful to map specific focal habitat types or species. The spatial scale of remotely sensed data may be coarser or finer than the spatial scale of key ancillary environmental datasets. For instance, ancillary datasets on site conditions for the local scale typical of Natura 2000 habitats in Europe vary from 1:25,000 to 1:50,000 (e.g., for some soil maps) to 1:1,000 to

1:5,000 for some field generated habitat maps and Digital Elevation maps (Weiers et al., 2004; Förster and Kleinschmit, 2008; Bock et al., 2005; Lucas et al., 2011). Förster and Kleinschmit (2008) found that ancillary datasets on site conditions such as altitude, aspect, slope and soil type were able to improve the classification of forest habitats in a pre-alpine area in Bavaria using QuickBird data. However, such information may be more useful for classifying habitat types that have distinct and defined state factors (e.g., alluvial forests). Habitats with clear boundaries (e.g., grassland and agriculture) can generally be mapped with greater accuracy (Bock et al., 2005; Lucas et al., 2007; Förster and Kleinschmit, 2008).

Tradeoffs between spatial and spectral resolution also need to be kept in mind. The currently popular VHR platforms of QuickBird, IKONOS, GeoEye and WorldView-2 lack shortwave infrared and thermal infrared bands, which have proved to be useful for discriminating some vegetation types using, for example, Landsat sensor data (Nagendra, 2001). Thus, Gao (1999) found that 30 m Landsat data were more useful than 10 m SPOT data for discriminating mangrove forests in New Zealand, simply because of their spectrally important thermal infrared bands, despite the lower spatial resolution of these bands. Oldeland et al. (2010) successfully used 5 m resolution HyMap hyperspectral data to map differences in vegetation within a challenging, low contrast semi-arid rangeland in central Namibia, using a fuzzy approach to achieve classification accuracies of 98%. Thenkabail et al. (2004) found that the spaceborne hyperspectral imager Hyperion, with 196 bands and a spatial resolution of 30 m, significantly outperformed a number of other optical sensors – Landsat ETM+ with 6 bands and a spatial resolution of 30 m, IKONOS with 4 bands and a spatial resolution of 4 m, and the Advanced Land Imager (ALI) with 9 bands and a spatial resolution of 30 m – in terms of its ability to distinguish between forest successional classes in the rainforests of Congo. The shortwave infrared bands of Hyperion, which represent a region of the electromagnetic spectrum not covered by the other sensors, appeared to be especially important for habitat mapping in this location.

Although Hyperion was the first spaceborne imaging spectrometer for civilian use, other airborne hyperspectral sensors such as NASA's Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) have stimulated a number of monitoring studies (Turner et al., 2003; Papes et al., 2009). Schmidtlein and Sassin (2004) utilized the AVIRIS-2 with bands between 400–874 nm and a spatial resolution of 2 m to successfully map floristic gradients in a Bavarian grassland, which can be useful to separate different grassland habitats. A recent study by Haest et al. (2010) in a Belgian heathland Natura 2000 landscape demonstrated the ability of airborne hyperspectral line-scanner radiometer (AHS-160) imagery with 63 visual and near-infrared bands with a spatial resolution of 2.4 m for mapping habitat extent and quality, despite the relatively low levels of contrast between heathland habitat types. Increasing temporal resolution can facilitate the accurate delineation of spectrally similar habitats in areas with seasonal environmental fluctuations, particularly if images are selected at critical stages that emphasize phenological differences between them (Nagendra, 2001). de Colstoun et al. (2003) found that the discrimination of 11 different land cover types in a recreational park in the USA increased substantially when using multi-season Landsat ETM+ imagery. Lucas et al. (2007) also used multi-date Landsat TM imagery to successfully distinguish a range of semi-natural habitats and agricultural land covers. Acquiring different remote sensing datasets at multiple, spectrally and phenologically important seasons poses a challenge however, especially in areas where cloud cover is an issue. Nevertheless, habitat mapping in Wales was conducted using multi-temporal imagery, including those that partly contained cloud (Lucas et al., 2011).

Finally, issues of radiometric resolution should be considered when selecting remote sensing data for habitat mapping. Rao et al. (2007) observed a small but definite increase in classification accuracy when a simulated 12-bit Indian Remote Sensing satellite (IRS) LISS 3 dataset was used instead of the original 7-bit dataset. The greatest improvement in classification accuracy was observed for more heterogeneous land use/land cover classes. Legleiter et al. (2002) also found a slight improvement of the overall accuracy in the classification of stream habitats when using data of a higher radiometric resolution, although this was secondary to the improvement delivered by an increase in spectral or spatial resolution.

Active remote sensing data, including SAR and LiDAR, provide information that is clearly complementary to optical sensors (Strittholt and Steininger, 2007). SAR data represent a useful alternative to passive remote sensing in areas where cloud cover is high and in specific habitats such as wetlands and seasonally inundated forests, although these data are especially challenging to use successfully in areas of high topographic variability. Radar and also LiDAR can assist in discriminating between habitat types based on their three-dimensional (3D) structure and biomass (Koch, 2010), which can be related to age, succession and species composition (Lim et al., 2003; Strittholt and Steininger, 2007; Mallet and Bretar, 2009). The ALOS PALSAR and RADARSAT-2 SAR have shown great potential for mapping wildlife habitat, particularly when combined with optical remote sensing through data fusion (Wang et al., 2009a). In particular, ALOS PALSAR L-band SAR allows detection of forest and non-forest and retrieval of above ground biomass (Rahman et al., 2010; Karjalainen et al., 2009). X- and C-band data can also be used to discriminate non-woody vegetation based on differences in, for example, stem and/or leaf size and orientation. The archives of SAR data (e.g. the European Space Agency (ESA), ENVISAT, the JERS-1 SAR and ALOS PALSAR) also provide a valuable resource for multi-temporal analysis and change detection. The fusion of optical and SAR data is beneficial for separating land cover types that are structurally distinct but spectrally similar (Treuhaft et al., 2004) and hence challenging to distinguish through optical remote sensing alone (Wang et al., 2009a; Zhu et al., 2011).

In conclusion, while VHR datasets are frequently mentioned as being the ideal option for fine scale mapping of habitats with high spatial heterogeneity, high resolution imagery such as Landsat, SPOT, ASTER and IRS are often sufficient for the purpose of habitat mapping over large areas, even in complex fine-scale habitat mosaics (Lucas et al., 2011). VHR and high resolution datasets suffer from problems of shadowing from and within objects and mixed pixels, and can be expensive and time consuming to procure and process. Hyperspectral imagery, though technically challenging, holds considerable promise for habitat mapping, especially in cases of high habitat and species diversity and fine-scale successional change. Recent VHR satellites such as WorldView-2 are beginning to open up the possibility of combining high spatial and spectral resolution in one same platform (Nagendra and Rocchini, 2008). Active remote sensing through SAR and LiDAR also holds great potential for the mapping and identification of structurally complex habitats and in areas where there is high and/or frequent cloud cover (in the case of SAR). Data fusion techniques that enable the integration of information from both active and passive sensors hold particular promise for habitat mapping and monitoring.

3.2. Assessing habitat degradation

Assessing the more cryptic and subtle process of habitat degradation is even more challenging than habitat mapping, often involving sub-canopy changes in structure, species composition and/or structure that are difficult to detect (Ingram et al., 2005; Joseph et al., 2011). Yet, habitat modification and degradation tends to be much more widespread even in seemingly intact landscapes – thus, developing methods to quantify and monitor changes of proxies for habitat quality/pressures are critical for adaptively managing protected areas. However, there has been comparatively much less research on this topic.

Changes in the spatial and temporal patterns of vegetation functioning can be used to support the detection of habitat modification and landscape change (Garbulsky and Paruelo, 2004). In the National Park network of Spain, the NDVI derived from NOAA/AVHRR was used to assess changes in photosynthetic activity between 1982 and 2006, with the contrast between growing and non-growing seasons increasing over the period (Alcaraz-Segura et al., 2009). Although the coarse spatial resolution (typical of the high temporal resolution sensors required for detailed phenological studies) is not appropriate for local scale monitoring of individual habitat patches, these products may provide early warning of regional scale ecological change and support decisions on the allocation of further resources for more detailed spatial assessments. Remote sensing data also provide insights into the impacts of climatic variability through analysis of changes in the extent and condition of vegetation (e.g. phenological shifts and species ranges shifts). For example, time-series of NDVI data have been used to indicate changes in LAI globally, with these reflecting human-induced and natural events and processes, including those related to climatic fluctuation (Silang et al., 2010).

Souza et al. (2003) combined information from the IKONOS and SPOT-4 sensors to differentiate intact forest from logged, degraded and regenerating forest using a decision tree classifier, with 86% overall accuracy. Ingram et al. (2005) used Landsat ETM+-derived information in conjunction with field measurements to predict tree basal area, associating this with human disturbance. Rouget et al. (2006) calculated intra-annual variances in NDVI from Landsat imagery to locate degradation due to livestock grazing in southern Africa. Linderman et al. (2005) mapped the availability of understory bamboo, through innovative neural network analysis of Landsat TM imagery, to estimate giant panda habitat suitability. Theau et al. (2005) also used Landsat TM to derive information on lichen land cover in northern Canada, with this being an indicator of caribou habitat, using Enhancement Classification methods and Spectral Mixture Analysis.

In a very different desert habitat in China, Chen et al. (2005) used Landsat ETM+ to identify biological soil crusts, which represent communities of important species such as lichens and mosses. As crusts are extremely susceptible to erosion related to desertification and climate change, this research identified an important monitoring capability for tracking desertification in cold deserts. In a hot desert in New Mexico, Muldavin et al. (2001) used a grassland biodiversity index computed from Landsat TM to accurately identify grasslands with limited degradation and high conservation value. Their results suggested that traditionally used indices of vegetation, including NDVI and tasselled-cap greenness, may be less useful in arid regions. Tong et al. (2004) used Landsat TM data in combination with field studies and ancillary vegetation datasets to develop an index of steppe degradation in Inner Mongolia, with this information being relevant to management interventions.

Hyperspectral imagery has also been used widely to assess habitat degradation, perhaps most commonly through assessments of habitat stress based on parameters such as nutrient deficiency (Joseph et al., 2011). Hyperspectral bands can enable the assessments of changes in chemical and structural traits including alterations in the level of chlorophyll, nitrogen, phosphorus and other foliage compounds, that can be linked with variations in enabling environmental factors such as soil quality (Townsend et al., 2008). Haest et al. (2010) used the greater spectral resolution provided by airborne hyperspectral imagery (AHS-160) with a spatial resolution of 2.4 m to map habitat quality, using expert-defined indicators based on vegetation pattern within habitat patches. Spanhove et al. (2012) compared the potential of airborne hyperspectral imagery against field assessments to provide information on conservation status in two Natura 2000 heathland areas, finding that field estimates were able to explain up to 43% of the variation in fine-scale indicators of habitat condition, while information derived from remote sensing could explain up to 39% of the variation in fine-scale habitat indicators. In specific instances, when field assessments were susceptible to high inter-observer variability, remote sensing predictions provided a significant improvement, illustrating the potential for the further use of hyperspectral imagery for fine-scale mapping and monitoring of changes in habitat condition and quality. SAR and LiDAR imagery, with its ability to penetrate below the top vegetation canopy, can be very useful for monitoring habitat degradation. Kuplich (2006) used a combination of Landsat and SAR to differentiate between Amazonian forest patches in different stages of regrowth. The discrimination ability of SAR imagery alone was limited, but improved substantially when integrated with TM data. Waser et al. (2008) used VHR airborne imagery and LiDAR data to create early warning signals of tree and shrub encroachment into non-wooded habitats, such as mire, an approach of fractional cover analysis. Graf et al. (2009) used LiDAR imagery alone to derive information on the horizontal and vertical stand structure in a forest reserve in central Europe, mapping habitat suitability for an endangered forest grouse species and providing important management recommendations at the local scale. Hyde et al. (2006) integrated LiDAR, SAR, Landsat and/or QuickBird to map wildlife habitat quality in the Sierra National Forest (Sierra Nevada, California), finding that the combination of LiDAR and ETM provided the best results, while incorporating QuickBird and SAR resulted in marginal improvement. LiDAR was especially useful in estimating canopy height and biomass, two important indicators of habitat suitability in this ecosystem.

Landscape fragmentation, through the disruption of habitat connectivity, can impact species dispersion and habitat colonization, gene flows and population diversity, and species mortality and reproduction. Thus, quantitative analyses of changes in landscape structure have been used to provide early warnings of habitat degradation. For instance, effective mesh size, which describes the probability that any two habitat patches are connected in a landscape, was used to compare the relative impacts of different types of land use disturbance such as roads and agriculture in California (Girvetz et al., 2008). A similar approach was also found to be useful for monitoring anthropogenic and natural disturbance in the Swiss Monitoring System of Sustainable Development (Jaeger et al., 2008). Riitters et al. (2009) developed an additional indicator of landscape composition, the “landscape mosaic”, which described the composition of the landscape locally adjacent to each pixel, and used this to assess dominant drivers of disturbance and identify vulnerable locations in the southern United States. Morphological image processing (Vogt et al., 2007) is another approach that has been utilized to map internal and external fragmentation in protected areas in Italy. Mairota et al. (2012) suggest that the combined use of traditional landscape pattern analysis, morphological spatial pattern analysis and landscape mosaic analysis can be useful to obtain synthetic quantitative descriptors of landscape structure and provide baselines for habitat fragmentation monitoring, within and outside protected areas, again using a case study of a landscape in Italy.

3.3. Assessing species diversity and distribution

Obtaining early warning signals of changes in the occurrence and spread of key species is critical for managers (He et al., 2011). Invasions and modifications of habitat structure and condition by alien species also present an urgent problem for managers of many nature reserves (Vicente et al., 2011). Remote sensing data provide an effective and evident way to address these issues at multiple scales although, in general, species distribution patterns are easier to map at a broader scale compared to fine scale distributions (Kerr and Ostrovsky, 2003).

Despite the relatively low spatial resolution (30 m) of Landsat imagery, several studies point to the continued utility of this platform to predict the most commonly used surrogates to measure biodiversity (e.g. species richness and diversity). Gillespie (2005), studying tropical dry forests in southern Florida, found the NDVI to be more strongly correlated with evergreen rather than with deciduous species density, but more strongly correlated with deciduous rather than evergreen species richness. Combining metrics of landscape structure – in particular, estimates of forest patch area – with NDVI data provided a significant improvement in the accuracy of prediction of plant species richness. A study by Feeley et al. (2005) in a dry tropical forest in Venezuela, also found vegetation indices (NDVI, Infra Red Index and Middle Infra Red Index) with be correlated with species diversity indices, but not stand density. Nagendra et al. (2010a) found that spectral information from Landsat ETM+ was not strongly correlated with tree density in a dry tropical forest ecosystem, but instead appeared most sensitive to total species richness, followed by indices of tree species diversity.

Landsat and lower resolution datasets have also been used with success in a variety of other ecosystems. In a heterogeneous landscape in North and South Carolina, USA, Costanza et al. (2011) found that land cover heterogeneity, calculated using a land cover map at 30 m resolution, was not significantly related with local plant species richness. However, heterogeneity across different ecoregions was positively related to plant species richness, possibly because this provides a measure of the variability between different habitat types within an ecoregion. In a high diversity tropical forest in Borneo, Foody and Cutler (2006) used a neural network analysis of Landsat TM imagery to predict the spatial distribution of species richness with high success. Hernández-Stefanoni et al. (2011) used an innovative combination of remote sensing predictors of tree species richness derived from Landsat TM imagery in conjunction with kriging interpolation techniques to improve the accuracy of tropical species richness maps in a study conducted in Yucatan, Mexico. In western Africa, Torres et al. (2010) used Landsat TM imagery combined with landscape pattern analysis and predictive modelling to relate the occurrence and conservation of chimpanzee with forest patterns and dynamics. Mohammadi and Shataee (2010) have used indices derived from Landsat ETM+ to model tree species diversity in the Hyrcanian forests of Iran.

As with habitat mapping, VHR data sets are widely considered to hold great promise for species distribution mapping. Remote imagery from optical sensors has been largely used to map the distribution of canopy foliage, but the scope for animal species mapping is more limited. There have, however, been recent attempts in this regard (e.g. to utilize audio (acoustic) remote sensing to monitor amphibians (Sueur et al., 2012), and to use radar to track birds (Robinson et al., 2009)) – we do not discuss these in further detail as these technologies are largely in the development phase. In an innovative approach, St-Louis et al. (2006) used derived texture information from digital ortho-photographs, and combined this with information on other environmental attributes including elevation and coarse habitat type, to predict bird species richness in a semi-arid landscape of New Mexico. Hall et al. (2011) employed QuickBird with success to derive relationships with fine-scale plant species richness in a semi-natural grassland in Sweden, finding that species richness and species turnover were significantly associated with the NDVI, demonstrating a non-linear, U shaped relationship. Of all image-derived variables, the spectral heterogeneity in the near-infrared band had the greatest explanatory power in this field context.

There is a need for analysis at multiple spatial scales, as patterns that are hidden at some spatial scales may be revealed at others (Rocchini et al., 2010). For instance, Kumar et al. (2009) found that spatial heterogeneity, as assessed by the satellite image-derived NDVI, strongly influenced butterfly species richness in a national park in the USA, but the strength of this relationship varied with spatial scale. Using high spatial resolution QuickBird imagery, Levanoni et al. (2011) confirmed this close relation between the local variability in NDVI (interpreted as a surrogate for spatial heterogeneity in productivity) and butterfly species richness along an altitude gradient in Israel.

Everitt et al. (2005) utilized QuickBird to map the distribution of invasive giant reed populations along the Rio Grande in Texas. This species was particularly easy to distinguish due to its characteristic association in large clumps, and they achieved very high accuracies of 86–100%. Gillespie et al. (2008) reviewed a number of other studies that utilize VHR data to map specific tree species within temperate and mangrove forests, concluding that these datasets provided important information for managers on the distribution of selected species and rates of tree mortality.

Sánchez-Azofeifa et al. (2011) used QuickBird imagery to map the distribution of a *Tabebuia* tree species in the Barro Colorado island in Panama, relying on images covering a short 2-day span of synchronized flowering. They successfully detected flowering trees, but missed a large proportion of trees not flowering at the time of image acquisition. Although this species was not an invasive, the authors conclude that this type of approach can be adapted to identify the location of individuals of invasive species when they are flowering. Somodi et al. (2012) developed a low-cost, simple approach to map the distribution and monitor the spread of the invasive woody species *Robina pseudoacacia* in a mixed wooded habitat in Slovenia, using a combination of Landsat ETM$_{-}$ imagery and 1:5000 airborne orthophotographs from two seasons – summer and spring. The best results were obtained when using the orthophotograph taken in spring, when the species being mapped was flowering – and improved further when a GIS map of forest distribution was used to filter specific locations for mapping.

In contrast to the conclusions of these studies, Fuller (2005) attempted to map *Melaleuca quinquenervia*, an invasive tree species in southern Florida, using IKONOS imagery, but concluded that VHR imagery was unsuitable because of the very small pixel sizes, increasing the variability between different tree canopies and hence difficulty in identifying the tree crowns of the species under study. This was particularly challenging at the early stage of invasion where densities were low, but when it was most feasible and useful for managers to manage invasive plant species. In a dry tropical Indian forest, Landsat sensor data appeared more suited to tree species mapping than IKONOS, because of the inclusion of the short wave infrared channel (Nagendra et al., 2010a). Similar conclusions were drawn in a recent review by He et al. (2011). Nagendra and Rocchini (2008) and Lucas et al. (2008b) also pointed out the challenges of dealing with VHR data for discriminating individual plants and trees, as shadow effects caused by tree canopies begin to predominate.

Spectral heterogeneity can also play a very important role in assessing habitat and species diversity within habitats. Oldeland et al. (2010) mapped seven different types of vegetation assemblages in a relatively low-variation rangeland landscape in Namibia using airborne hyperspectral imagery, finding added improvement in accuracy when species abundance as well as composition was considered. Ward et al. (2012) predicted plant communities of floodplain grasslands and salt marshes in Estonia with an accuracy between 60 and 100%. In a review of the application of hyperspectral imagery for species diversity assessment in forests, Ghiyamat and Shafri (2010) concluded that wavelet transforms applied to hyperspectral data can be very useful in discriminating between different species in tropical forests. Sluiter and Pebesma (2010) found that the classification of semi-natural Mediterranean vegetation communities in southern France using ASTER data improved when high spatial resolution hyperspectral HyMap data were incorporated, but only to a very small extent. In a moist grassland in a floodplain in central Japan, hyperspectral images collected at 1.5 m spatial resolution and with 68 contiguous bands in the 398–984 nm wavelength ranges acquired by the Airborne Imaging Spectrometer for Applications (AISA) Eagle, were used successfully to map grassland communities of differing understory species composition, based on the ability of the sensor to discriminate differences in density of the dominant top-canopy species present in each community (Ishi et al., 2009).

A number of other studies have used spectral heterogeneity as a proxy for species diversity, as summarized in a recent review by Rocchini et al. (2010). The spectral distance between locations can be a powerful predictor of variation in species composition (Rocchini and Cade, 2008). Hyperspectral imagery, which provides additional power for spectral discrimination, should hold an increased capacity for species mapping in heterogeneous and species rich ecosystems and landscapes.

Clark et al. (2005) used imagery from the airborne HYperspectral Digital Imagery Collection Experiment (HYDICE) sensor, with 210 bands in the 400–2500 nm range, and a spatial resolution of 1.6 m, to examine the spectral separability of seven emergent tree species in a tropical rain forest in Costa Rica. Within-species spectral variability was significantly lower than between-species spectral variability in all spectral regions, but the maximum separability between species was observed in the near infra-red region. Species classification accuracies using hyperspectral imagery were significantly higher than accuracies achieved using simulated multispectral imagery. This study focused on emergent trees, which tend to be less influenced by problems of shadows or spectral overlaps with crowns of adjacent tree species, and the approach may be difficult to extrapolate to larger tropical forest areas.

Lucas et al. (2008a) discriminated trees to the species or genus level by extracting spectra from the sunlit portion of crowns delineated within 1 m spatial resolution Compact Airborne Spectrographic Imager (CASI) data in Australian woodlands. They found an improvement in classification accuracy after incorporating shortwave infrared data from 2.6 m resolution HyMap data. Papes et al. (2009) provided the first instance of use of Hyperion data to map the crowns of emergent trees in tropical forests, using imagery from dry and wet seasons. A relatively narrow set of bands was sufficient for discriminating between five non-related taxa, with 100% accuracy achieved. Pengra et al. (2007) also used Hyperion to successfully map the presence and extent of an invasive tall grass, *Phragmites australis*, that impacts native wetland habitat in North America.

Timing the acquisition of remotely sensed datasets to coincide with critical phenological stages of flowering or leaf senescence can be important when mapping invasive species (He et al., 2011). For instance, Ramsey et al. (2005) demonstrated the utility of spaceborne hyperspectral data from Hyperion to map Chinese tallow trees, *Triadica sebifera*, an invasive species, in a coastal wetland in southwestern Louisiana to accuracy levels of 78%. Andrew and Ustin (2008) used 3 m 128-band airborne hyperspectral HyMap imagery to successfully discriminate invasive pepperweed *Lepidium latifolium* in relatively simple wetland and riparian habitats in the USA, but failed to do so in more challenging complex habitat mosaics.

A number of other studies of invasive species assessment, reviewed by He et al. (2011), concluded that hyperspectral images are particularly useful for mapping individual species when the invader shows a scattered distribution of low density. Collecting imagery that corresponds to unique phenological stages, such as flowering or senescence, increases the likelihood of accurate identification. Approaches to classification such as end-member analysis can be useful in discriminating between pure stands of conifers and deciduous species, as shown with HyMap data (Darvishsefat et al., 2002). A study of ten tree species in Kruger National Park (Cho et al., 2010) similarly found that, while intra-species spectral variability was considerable, its impacts on classification accuracy could be minimized by using multiple end-members for each species.

Accurate discrimination of all top-canopy species is unlikely, particularly in high biodiversity forests of the tropics and subtropics where there is a substantial amount of overlap between leaves and branches of individual plants and trees from different species. Consequently, the reflectance spectra from these different tree crowns will result in mixed pixels. This problem is unlikely to disappear even if hyperspectral image resolution and noise to signal ratios improve significantly in the future (Nagendra, 2001; Fuller, 2007). Asner and Martin (2009) have suggested the potential for a new approach of "airborne spectranomics" combining spectral and chemical remote sensing for the high resolution mapping of canopy forest species. This approach utilizes the ability of recently developed High-fidelity Imaging Spectrometers (HiFIS) to provide two-dimensional hyperspectral imaging in addition to a third dimension that provides a detailed spectroscopic signature of plant canopies. Algorithms are still being developed to analyse these data and link canopy chemistry to species identity. Further, since fine-scale variations in canopy three-dimensional structure lead to shadowing and brightness, increasing within-canopy spectral variation, new sensors are being developed to integrate HiFIS with LiDAR technology, which are anticipated to further improve the prospects for mapping canopy species (Asner and Martin, 2009). High-fidelity imaging spectroscopy, which provides very small pixel sizes of less than a meter, coupled with very high spectral resolution through a large number of narrow bands, can also provide major advances towards the goal of mapping tropical forest diversity – especially when coupled with LiDAR (Townsend et al., 2008). In a recent review, Koch (2010) suggested the utility of a multi-sensor approach, using optical data to delineate tree crowns and identify possible tree species type, and LiDAR to corroborate this by assessing tree height, to improve species identification.

The use of LiDAR for tree species mapping has been relatively limited to date (Koch, 2010). A combination of crown volume measurements taken at different tree heights, and measurements of tree height and intensity distribution, can be used for species mapping. A study in Finland found that Scots Pine and Norway Spruce were classified to an accuracy of 83% and 90% respectively, while birch trees were confused with the other species (Vauhkonen et al., 2010). Asner et al. (2008) used a combination of airborne optical and active remote sensing to map five invasive plant species in Hawaii. This fusion of datasets enabled them to identify transformations in 3-dimensional forest structure due to invasives replacing native plants at mid-canopy, understory and ground levels. Several studies have also used LiDAR successfully to monitor specific bird species or, less often, mammal species by modelling species-habitat relationships, as reviewed in Vierling et al. (2008).

These studies also clearly establish the importance of *in situ* data on species distribution for accurate interpretation of imagery. Thus, it is important to have well designed programs of field data collection that maximize the use of data for remote sensing interpretation and conservation assessments. *In situ* field sampling networks therefore need to be designed in combination with remote sensing using, for instance, stratified sampling designs to carefully assess species distributions across different habitat types and enhance interpretative power (Nagendra, 2001).

3.4. Tracking pressures and threats

While there can be many types of threats to conservation depending on the landscape, context and time period of focus, the more common types of disturbance observed in and outside protected areas include urbanization, road construction, mining, logging, agriculture, fire, invasion by alien species, hunting, grazing and drought (DeFries et al., 2005; Nagendra, 2008). An in-depth discussion of the use of remote sensing to detect invasive plants is provided in Section 3.3 above. Remote sensing datasets of medium to fine spatial resolution can also provide important information on the "signature" of human pressure related to land use, management and other disturbances in and around protected areas such as logging roads and burn scars (Fuller, 2007). Spatial datasets that provide information on aspects such as road networks, human and livestock population densities, agriculture in ecological vulnerable areas, air quality or point sources of pollution can greatly enhance the potential of remote sensing to provide pressure/stressor assessments. Ingram et al. (2005) used Landsat ETM+ imagery in conjunction with field plots to assess climatic and human pressures on forest biomass, relating the relatively low impact of a road bisecting the forest on basal area to the lack of mechanized logging in this forest. Nagendra et al. (2010b) also used Landsat TM and ETM+ imagery to find a clear signal of forest fragmentation and deforestation at the periphery of an Indian tiger park because of extraction by local residents of villages outside the boundary. Applying landscape pattern analysis to a land cover time series derived from Landsat imagery, Pôças et al. (2011b) were able to detect a trend for increased landscape fragmentation in high nature value mountain farmland in northern Portugal. Asner et al. (2004) used sub-pixel fractions to estimate the percentage of shade in pixels, correlating this with tree gaps caused by selective logging in the Amazon. Blanco et al. (2009) used Landsat TM to compare the impacts of continuous grazing against a rest-rotational system of grazing in a rangeland in Argentina. In Amazonia, the time-series classifications of Landsat sensor data enabled the reconstruction of fire and land-use history (Prates-Clark et al., 2009), with these collectively dictating the pathways of tropical forest regeneration and the capacity of these forests to recover biodiversity. The presence of the shortwave infrared band in AVHRR imagery, and therefore presumably also in Landsat data, is also considered to be critical for identifying the impact of drought on vegetation (Boyd et al., 2002).

Fire is an important driver of vegetation dynamics in many landscapes (Neary et al., 1999; Hudak and Brockett, 2004). A number of different remote sensing datasets, ranging from coarse scale 1 km AVHRR data to VHR images, have been employed to map fires (Kerr and Ostrovsky, 2003). Overall, the time of image acquisition appears to be more critical for fire studies than the spatial or spectral scale of imagery. MODIS has been widely used at regional scales for automated mapping of fires. Its pixel size of 250–500 m makes it unsuitable for local scale studies, but useful for longer term strategic regional planning (Lentile et al., 2006). Using a national fire map derived from Landsat 5 TM images, Nunes et al. (2005) confirmed that wildfires burn land cover types selectively in Portugal, since there is a marked positive bias towards shrublands over forest areas, while agricultural areas are clearly avoided.

VHR datasets can be very important to detect fine scale disturbances such as urbanization and human movement, mapping tree falls, and small scale pest attacks (Fuller, 2007). Allard (2003) used IKONOS data to map very fine scale impacts of grazing in a dry dwarf shrub heath in a mountainous landscape in Sweden, detecting erosion due to grazing at low levels that were easy to manage. Asner et al. (2002) used IKONOS to map the crown diameter of the largest trees in an Amazonian forest, as these trees were most commonly targeted by loggers. VHR datasets can also be very useful for studying fine scale pollution sources and their impact on wetlands and water bodies (e.g. Lee et al., 2010). For some kinds of disturbances that have an extremely short and focused temporal span, such as wildfires, cyclones or flash floods, high temporal resolution is required so that before and after studies of habitat distribution and condition can be conducted as close to the event as possible, for maximum information.

Hyperspectral information may also be useful in specific instances such as when studying foliage discolorations caused by specific pest attacks (Coops et al., 2007). Studies in Wales (Breyer, 2009) have suggested that the red edge wavebands are most sensitive to grass biomass and hence grazing levels and the availability of this waveband on several sensors (e.g., WorldView-2) may provide an opportunity for detecting grazing pressure. SAR data can also be used to indicate disturbance and deforestation patterns. For example, Lucas et al. (2008b) established the use of ALOS PALSAR data and Landsat-derived Foliage Projected Cover (FPC) for detecting dead standing trees and patterns of clearing in Queensland, Australia. Siegert et al. (2001) used data acquired by a high resolution (25 m) SAR on board the ERS-2 satellite, to map patterns of fire damage in forests in Indonesia and relate these to management categories.

4. Discussion and conclusions

The research cited in the previous sections has demonstrated the utility of remote sensing to provide spatial data for managers of protected areas, generating information on changes in habitat area, habitat degradation, alterations in species diversity and distribution, and trends in pressures and threats. As indicated in Table 1, and corroborated by other studies (Newton et al., 2009), the vast majority of studies have used Landsat TM/ETM+ images to assess changes in and around protected areas, highlighting the continued utility of these data and the invaluable historical record that now covers a period of four decades. In recent years, VHR datasets have been widely promoted for habitat and species monitoring, yet this review has established that whilst such datasets provide a greater level of detail, the extraction of information is often compromised by, for example, shadowing (e.g., from trees, terrain). Whilst more habitat categories can often be resolved, the issues surrounding spectral mixing still remain despite the higher resolution. The lack of a shortwave infrared band in many VHR datasets including IKONOS, QuickBird and GeoEye has significantly hampered their potential for monitoring complex environments with a high diversity of species (e.g., tropical forests) or spectrally homogeneous environments of low diversity (e.g. heathlands). However, the recent advent of satellite sensors such as WorldView-2 with its additional coastal, yellow, red edge and near infrared bands is anticipated to provide benefits over other VHR sensors observing only in the visible blue, green, red and/or near infrared. The use of multi-temporal datasets acquired during periods where spectral discrimination of vegetation types is maximally possible (e.g., during periods of phenological differentiation such as senescence or flowering) can further assist habitat classification.

In recent years, the benefits of using hyperspectral, LiDAR and SAR data for discriminating species within vegetation communities and habitats have increasingly been realised. LiDAR has proved particularly useful for understanding habitat degradation, tracking more subtle changes in structure and providing information on below-canopy pressures and threats (e.g., in highly biodiverse tropical forests). However, for many tropical regions, the capability for acquiring data from these sensors is limited at least at the spatial resolutions required for habitat monitoring. In the coming years, it is anticipated that such datasets will become more available as new satellite sensors are launched and remote sensing analysts further develop the necessary algorithms to process these effectively.

Table 1
Summary of active and passive remote sensing data useful for protected area monitoring.

Sensor	Habitat mapping and change detection	Assessing habitat degradation	Biodiversity assessment	Tracking pressures and threats
Coarse spatial resolution (e.g., MODIS, AVHRR)	Not very useful	Near-real time alerts of deforestation in threatened forests (e.g., Amazon; Joseph et al., 2011); Mapping overall changes in photosynthetic activity to provide early warnings of regional ecological change and climate change (Alcaraz-Segura et al., 2009; Silang et al., 2010)	Not very useful	Tracking fires and changes in overall photosynthetic activity (Boyd et al., 2002; Lentile et al., 2006; Alcaraz-Segura et al., 2009)
Medium to high spatial resolution (e.g., Landsat, IRS, SPOT)	Captures broad extent and spatial patterns of habitats (de Colstoun et al., 2003; Lucas et al., 2007, 2011; Varela et al., 2008; Pôças et al., 2011a)	Broad scale loss and degradation of habitats (e.g., semi-arid vegetation degraded through desertification; useful input to habitat suitability models; Muldavin et al., 2001; Tong et al., 2004; Chen et al., 2005; Ingram et al., 2005; Linderman et al., 2005; Theau et al., 2005)	Indicators of overall species richness and diversity (Feeley et al., 2005; Gillespie, 2005; Foody and Cutler, 2006; Mohammadi and Shataee, 2010; Nagendra et al., 2010a,b; Torres et al., 2010; Costanza et al., 2011; Hernández-Stefanoni et al., 2011)	Identifying disturbances in protected areas (e.g., urbanization, road construction, mining, logging, agriculture, fire, alien species, hunting, grazing and drought; Asner et al., 2004; DeFries et al., 2005; Ingram et al., 2005; Nunes et al., 2005; Fuller, 2007; Nagendra et al., 2008, 2010a,b; Blanco et al., 2009; Prates-Clark et al., 2009; Pôças et al., 2011b)
High temporal resolution data (multi-season data or images corresponding to specific seasons)	Separation of habitat types spectrally similar in single date imagery (Lucas et al., 2007, 2011)	Intra-annual variances in retrieved measures of biophysical properties (e.g., productivity; Rouget et al., 2006)	Information on invasive species and other species of interest (e.g., using images acquired corresponding to critical phenological stages of flowering or leaf senescence; Everitt et al., 2005; Ramsey et al., 2005; Andrew and Ustin, 2008; Sánchez-Azofeifa et al., 2011; He et al., 2011).	Detection of specific events (e.g., selective logging, fires) achieved through greater frequency of observation
Very high spatial resolution (e.g., IKONOS, QuickBird, GeoEye, WorldView-2)	Mapping successional fine-scale homogeneous habitats, ecotones and mosaic areas (Bock et al., 2005; Comber et al., 2010), but with challenges of mixed pixel and object shadowing	Identifying fine scale degradation in forests (Souza et al., 2003)	Indicators of overall species richness and diversity (St. Louis et al., 2006; Kumar et al., 2009; Levanoni et al., 2011; Hall et al., 2011); Delineation of tree crowns/clumps to species level (Everitt et al., 2005; Gillespie et al., 2008; Sánchez-Azofeifa et al., 2011; Somodi et al., 2012). Problems of mixed pixels and shadowing of objects (Fuller, 2005; Nagendra and Rocchini, 2008; Lucas et al., 2008b; Nagendra et al., 2010a,b; He et al., 2011)	Detection of fine-scale disturbances (e.g., pollution, urbanization and human movement, mapping tree falls, and small scale pest attacks; Asner et al., 2002; Allard, 2003; Fuller, 2007; Lee et al., 2010)
Hyperspectral (e.g. ASTER, HyMap, AVIS-2, AHS-160)	Distinguishing habitat types in low-contrast environments, and identifying forest successional classes (Papes et al., 2009; Thenkabail et al., 2004; Prates-Clark et al., 2009; Oldeland et al., 2010; Schmidtlein and Sassin, 2004; Haest et al., 2010)	Assessment of habitat stress based on changes in chemical composition of foliage, which can be related to parameters such as nutrient deficiency and changes in soil (Townsend et al., 2008; Joseph et al., 2011).	Differentiation of plant communities that are spectrally similar (Ishi et al., 2009; Ghiyamat and Shafri, 2010; Oldeland et al., 2010; Sluiter and Pebesma (2010); Ward et al., 2012). Mapping top canopy trees to species or genus level and identifying invasive species (Darvishsefat et al., 2002; Clark et al., 2005; Pengra et al., 2007; Lucas et al., 2008a; Papes et al., 2009; Cho et al., 2010; He et al., 2011); Relating spectral heterogeneity to species richness and diversity (Rocchini and Cade, 2008; Rocchini et al., 2010; He et al., 2011).	Identifying disturbances (e.g., pest attacks that lead to changes in foliage color, and fine-scale modifications in grass biomass due to disturbances such as grazing; Coops et al., 2007; Breyer, 2009)
Active remote sensing data – e.g. SAR, LiDAR	Discriminating structurally complex habitats (e.g., forests) based on 3D structure, either alone or in combination with optical remote sensing (Lim et al., 2003; Treuhaft et al., 2004; Strittholt and Steininger, 2007; Rahman et al., 2010; Karjalainen et al., 2009; Mallet and Bretar, 2009; Wang et al., 2009a; Koch, 2010; Zhu et al., 2011)	Monitoring habitat degradation, including within canopy (Kuplich, 2006; Hyde et al., 2006; Waser et al., 2008; Graf et al., 2009)	Floral and faunal diversity in habitats (e.g., forest) with complex three-dimensional structure (Asner et al., 2008; Koch, 2010; Vauhkonen et al., 2010).	Detecting dead standing trees, patterns of clearing and patterns of damage caused by fire (Siegert et al., 2001; Lucas et al., 2008b)

Techniques and software for processing these data are also likely to become more available in future years, and the increase in open source material will benefit many managers of protected areas in countries where funding is more limited.

While the research reviewed primarily highlights the role that remote sensing can play in assisting protected area managers to characterise and map habitats and monitor change, the data generated can also provide information on modifications of ecosystem conditions related to climate change (e.g. community traits). If coupled with "climate space" shift regional scale scenarios, such as those proposed by Wiens et al. (2011), such approaches might be of great use for strategic planning aimed at anticipating possible shifts of conservation targets from protected areas due to species migration and setting out measures to identify new candidate sites for protection (Hannah et al., 2007), as well as assisting target species migration whilst controlling the expansion of invaders. Thus, remote sensing can offer a means of responding to the "hotspots of opportunity" described by Wiens et al. (2011) by means of enhancement of the conditions that enable and facilitate functional links between areas that are currently protected. For this, there is a need for remote sensing analyses to be integrated with models (e.g., of species distributions) as well as accurate, time-matched *in situ* datasets to develop and validate the models and conclusions. Unless the spatial grain, extent and timing of remote sensing data and *in situ* data and models are well matched, the robustness of conclusions on management effectiveness, and the interpretative power of the analytical techniques used, will be limited. Remote sensing interpretation needs to be grounded in field data, and this is an important concept that is critical for effective adaptive management and monitoring.

In many situations, the need to improve the condition of protected areas relies first upon an assessment of the existing state of vegetation which can then assist understanding of how this may be best managed to improve its condition in the future, using principles of adaptive management as discussed previously. As an example, Prates-Clark et al. (2009) used time-series of Landsat sensor data acquired north of Manaus, Brazil, to establish the conditions imposed by forest clearance mechanisms and agricultural land management prior to abandonment. Different land use intensities were shown to lead to different pathways of tropical forest regeneration, as determined by the composition of the pioneer community, and their ability to recover the carbon and biodiversity lost during clearance of the original forest. Such information could potentially play a key role in landscape planning at an Amazon-wide level by identifying those areas that are either regenerating or still in agriculture and which would be most suited to be kept in production or managed to restore ecosystem values. Similarly, in Australia, Lucas et al. (2008b) identified different methods of clearing savanna woodlands using a combination of airborne radar and Landsat-derived Foliage Projected Cover (FPC), information which can be used to establish the likely composition of species in the regenerating forests and the time taken for these to revert to the mature state. In the Brigalow Belt Bioregion of southeast Queensland, these same datasets can be used to identify areas of regrowth at different stages of development and sites where the implementation of management strategies (e.g., thinning) could promote reestablishment of the forest or increases in structural diversity and biomass and also biodiversity (Bowen et al., 2009; Dwyer et al., 2010).

Remote sensing data can also be very useful in helping managers identify early warning signs of climate change at regional (Alcaraz-Segura et al., 2009; Silang et al., 2010; Altamirano et al., 2010) and local scales (Lucas et al., 2008a,b), based on early identifications of changes in plant physiology and phenology. The impact of these environmental changes may be minimized through early identification using combinations of satellite remote sensing data coupled with targeted field management (Jump et al., 2010). Such information may be particularly useful in marginal areas (e.g., deserts, semi-arid areas) or in mountainous regions or latitudes where distinct vegetation zonation occurs.

In many countries, forests are fragmented and often located within a mosaic of agricultural land (e.g., Hill and Curran, 2003). However, studies using remote sensing have often focused on mapping the extent of forest cover or classifying land covers within protected areas with less emphasis placed on the landscape that is surrounding them. Remote sensing data can however be used to indicate the spatial pattern and condition of these fragments, the causes of fragmentation (e.g., whether human-induced or natural) and the type and condition of land covers which could potentially be used to link important habitat patches. As an example, in the Biological Dynamics of Forest Fragments Project (BDFFP; Laurance et al., 2011) in Amazonas State, Brazil, fragments of forest which were isolated during clearance operations rapidly became surrounded by secondary forests, with the development of these observable using time-series of Landsat sensor data (Prates-Clark et al., 2009). These regrowth forests provided connections between the fragments and the larger extent of undisturbed forests, thereby facilitating movement of fauna and flora. Hence, satellite sensor data can be used to better understand the impacts of the surrounding and changing landscape on their longer term role of forest fragments. These data can also be used to identify events or processes that may be occurring before it is too late or expensive to undertake remediation measures.

The success in using remote sensing data for mapping habitats and monitoring change, both within protected areas and also in the surrounding landscape, is dependent upon the provision of information that is useful to those charged with management. In many cases, conservation organisations are presented with maps, often of land cover, which do not adequately represent the habitats occurring and of importance to biodiversity. Use is also compromised by inappropriate classes, the lack of spatial detail and the use of hard classifications where often a transition or gradient occurs between habitats. While a large number of maps exist at various scales, these are often of limited utility and hence may not be adopted. Furthermore, many maps are also generated once, with no capacity for updates and, where different sensor data are used for classification, inconsistencies occur and hence the detection of changes is often problematic. The development of habitat and species monitoring that facilitates routine mapping and monitoring is therefore desirable (Lucas et al., 2011). Representation of the 3D structure of habitats is also important, particularly in habitat suitability modelling and assessments of forest condition. Focus has often been on the two dimensional distribution of habitats (e.g., forests), with this frequently obtained using optical remote sensing data. Indeed, many landscape metrics and species distribution models consider only the type of forest occurring (e.g., broad-leaved, needle-leaved) and less consideration is given to the 3D structure. With the advent of active remote sensing data, namely LiDAR and lower frequency as well as interferometric SAR, the potential for obtaining information on the 3D state of vegetation has increased significantly and habitat models need to be developed to better integrate this information.

In conclusion, remote sensing can play a key role in characterising and mapping habitats within and surrounding protected areas and ultimately assisting their management. Whilst the Landsat sensors have been the workhorse of many monitoring programs and activities, new sensors are resolving more detail in the landscape in both two and three dimensions, and the increased frequency of observation by many is allowing changes to be better identified. These data can be used to inform on changes in the landscape which may have an adverse impact on biodiversity but also allow for long-term restoration of habitats (e.g., through replanting, establishment of corridors and/or promotion of regeneration) and protection from the adverse effects of factors such as climate change (Jones et al., 2009). Most importantly, these data can provide managers of protected areas with spatial and temporal information on the extent and condition of habitats and their response to change over varying time scales. Their use needs to be made standard practice. So far this has not happened, despite much discussion on the utility of remote sensing. This may be largely due to the technical challenges faced by managers in conducting and accurately interpreting image analyses, but also because of insufficient integration between the in situ data and expert knowledge provided by local ecologists and the technical expertise of remote sensing analysts. There is a need for ecologists, conservation biologists, policy makers, protected area managers, conservation consultants and practitioners ("experts") to be provided with a basic technical understanding of remote sensing. This would allow them to interact with remote sensing analysts to provide expert inputs for the proper collection and interpretation of data to fulfil their monitoring and planning requirements.

Simultaneously, the lack of utilization of earth observation data for conservation planning so far poses a challenge for the remote sensing community. One approach that has significant potential to bridge this gap is for remote sensing analysts to work with "experts" to take their inputs, and use these to develop semi-automated, operational tools for mapping and monitoring habitat extent and quality. In the process, "experts" can learn how to bring their practice closer to remote sensing needs. The BIO_SOS project (www.biosos.eu) aims to provide a step further towards this goal, by working towards protocols and pre-operational software to map changes in habitat extent and quality, and track human pressure on protected areas. The interdisciplinary approach of this project differs from previous ones largely focused on the use of remote sensing data for the semi-automated mapping of changes in land use and land cover (e.g. Fraser et al., 2009). Such an approach, as well as the products thereby generated, have the potential to make it easier for managers and practitioners with a basic technical understanding of remote sensing to generate information on conservation status routinely, quickly and relatively inexpensively, with reasonable levels of accuracy, that can be useful for adaptive management of protected areas as well as of their geographic context.

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