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Measuring and modelling biodiversity from space

Thomas W. Gillespie,[1]* Giles M. Foody,[2] Duccio Rocchini,[3] Ana Paula Giorgi[1] and Sassan Saatchi[4]

[1]Department of Geography, University of California Los Angeles, Los Angeles, CA 90095-1524, USA
[2]School of Geography, The University of Nottingham, University Park, Nottingham NG7 2RD, UK
[3]Dipartimento di Scienze Ambientali 'G. Sarfatti', Università degli Studi di Siena, Via Mattioli 4, 53100 Siena, Italy
[4]Jet Propulsion Laboratory, California Institute of Technology, 4800 Oak Grove Drive, Pasadena, CA, 91109, USA

Abstract: The Earth is undergoing an accelerated rate of native ecosystem conversion and degradation and there is increased interest in measuring and modelling biodiversity from space. Biogeographers have a long-standing interest in measuring patterns of species occurrence and distributional movements and an interest in modelling species distributions and patterns of diversity. Much progress has been made in identifying plant species from space using high-resolution satellites (QuickBird, IKONOS), while the measurement of species movements has become commonplace with the ARGOS satellite tracking system which has been used to track the movements of thousands of individual animals. There have been significant advances in land-cover classifications by combining data from multi-passive and active sensors, and new classification techniques. Species distribution modelling has been growing at a striking rate and the incorporation of spaceborne data on climate, topography, land cover, and vegetation structure has great potential to improve models. There have been significant advances in modelling species richness, alpha diversity, and beta diversity using multisensors to quantify land-cover classifications and landscape metrics, measures of productivity, and measures of heterogeneity. Remote sensing of nature reserves can provide natural resources managers with near real-time data within and around reserves that can be used to support conservation efforts anywhere in the world. Future research should focus on incorporating recent spaceborne sensors, more extensive integration of available spaceborne imagery, and the collection and dissemination of high-quality field data. This will improve our understanding of the distribution of life on earth.

Key words: biogeography, conservation planning, diversity modelling, remote sensing, species distribution modelling.

*Author for correspondence. Email: tg@geog.ucla.edu

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I Introduction

The Earth is undergoing an accelerated rate of native ecosystem conversion and degradation (Nepstad *et al*., 1999; Myers *et al*., 2000; Achard *et al*., 2002) and there is increased interest in measuring and modelling biodiversity from space (Nagendra, 2001; Kerr and Ostrovsky, 2003; Turner *et al*., 2003). Biodiversity can be defined as the variation of life forms within a given ecosystem, region or the entire earth. However, biodiversity is a multifaceted variable and so one that can be difficult to measure and express simply (Duro *et al*., 2007). Biogeographers have long-standing interest in the distribution of biodiversity over different spatial and temporal scales (Whittaker *et al*., 2001; Lomolino *et al*., 2004). In particular, biogeographers are interested in measuring or quantifying patterns of species occurrence, distribution, and distributional movements. Biogeographers are also interested in modelling or providing probability maps of species distributions and patterns of diversity.

The most accurate ways to collect biogeographical data on species distributions are intensive ground surveys or inventories of species in the field. High-resolution maps of species are available in the United Kingdom where inventories of plants and birds have been undertaken for over a decade at a 10×10 km resolution (Gibbons *et al*., 1993). Plant and animal distribution data are also available at a 50×50 km resolution in Europe, Australia, the USA, Canada, and South Africa (Kidd and Ritchie, 2006; Finnie *et al*., 2007). However, these inventories require skilled individuals, a significant amount of time in the field, and can be extremely expensive. Even in relatively well-studied areas, different field data sources can lead to dissimilar or biased maps of species distributions and diversity (Graham and Hijmans, 2006; Moerman and Estabrook, 2006; Pautasso and McKinney, 2007), and in areas such as the tropics species occurrence and distribution data are relatively coarse and not well collected (Phillips *et al*., 2003; Schulman *et al*., 2007b). Thus, there is currently a lack of high-resolution data and maps for a number of regions and biogeographers are continuing to research ways to map species distributions and diversity that could have significant applications for conservation planning (Foody, 2003; Whittaker *et al*., 2005).

Remote sensing has considerable potential as a source of information on biodiversity at landscape, regional, continental, and global spatial scales (Nagendra, 2001; Willis and Whittaker, 2002; Turner *et al*., 2003). The main attractions of remote sensing as a source of information on biodiversity are that it offers an inexpensive means of deriving complete spatial coverage of environmental information for large areas in a consistent manner that may be updated regularly (Muldavin *et al*., 2001; Duro *et al*., 2007). Despite its well-established attractions and potential, historically, remote sensing has been relatively underused in studies of biodiversity (Innes and Koch, 1998; Trisurat *et al*., 2000). Recently, however, there has been an increase in studies and reviews of bio-diversity taking advantage of advances in sensor technology or focusing on broad patterns in variables related to biodiversity (Kerr *et al*., 2001; Turner *et al*., 2003; Rocchini *et al*., 2007; Saatchi *et al*., 2008). These advances in remote sensing are generally divided into direct and indirect approaches (Nagendra, 2001; Turner *et al*., 2003; Duro *et al*., 2007). Direct approaches use spaceborne sensors to identify either species, such as the identification of tree species, or land-cover types, and directly map the distribution of species assemblages. Indirect approaches use spaceborne sensors to model species distributions and the distributions of diversity. Both approaches have significant applications for species and ecosystem conservation that have still not been completely developed to their full utility.

This research reviews recent and future advances in remote sensing that can be used by biogeographers to measure and model biodiversity patterns from spaceborne sensors.

First, we examine satellites currently being used to measure and model biodiversity from space. Second, we examine advances in direct approaches for measuring species and land-cover classifications. Third, we examine advances in modelling patterns of species and diversity. Finally, we examine the applications of remote sensing methods for conservation planning.

II Spaceborne sensors

There has been a dramatic increase in earth observation satellites and sensors over the last seven years that have been used to measure and model biodiversity from space (Table 1). Passive sensors, which record reflected (visible and infrared wavelengths) and emitted energy (thermal wavelengths), are most frequently used in biodiversity studies. The highest spatial resolution data comes from commercial satellites, such as QuickBird and IKONOS, which contain visible and infrared bands used in species mapping. The NASA Landsat series is the most widely used sensor for biodiversity studies due to the ease in which the data can be obtained, long time series, and low cost. The Landsat series has been used extensively in land-cover classifications, diversity models, and conservation studies. However, Landsat ETM+ began to malfunction on 31 May 2003, ending 31 years of continuous Landsat series data. Other satellites and sensors such as IRS, SPOT, and ASTER are becoming more common; however, the lower number of studies may reflect the higher cost and availability of the data. The MODIS and AVHRR sensors have provided extremely useful data for regional, continental, and global studies of land-cover classification and diversity models. These sensors also provide data on temperature, precipitation, and fire that have been incorporated into biodiversity studies.

Table 1 Satellites with passive or active sensors that can be used to measure and model biodiversity from space

Satellite (sensor)	Pixel size (m)	Bands	Cited in this review
Passive sensors		Spectral bands	
QuickBird 2	0.6, 2.5	5	7
IKONOS 2	1, 4	5	6
OrbView 3	1, 4	5	0
Landsat (TM, ETM+)	15, 30, 60, 120	7–8	42
IRS (LISS III)	5, 23, 70	5	4
EOS (ASTER)	15, 30, 90	14	3
SPOT	2.5, 10, 1150	5	2
EOS (Hyperion)	30	220	2
ALOS	2.5, 10	4	0
NOAA (AVHRR)	1100	5	8
EOS (MODIS)	250, 500, 1000	36	6
Active sensors		Bands	
SRTM	30, 90	X, C	5
QSCAT	2500	Ku	2
Radarsat	9–100	C	1
SIR-C	10–200	X, C, L	1
TRMM (TMI)	18000	X, K, Ka, W	1
ERS-2	26	C	0
Envisat (ASAR)	30	C	0

Radar is the most common active spaceborne sensor used in biodiversity studies. Radar sensors send and receive a microwave pulse in different wavelengths (ie, X-, C, L- bands) to create an image based on radar backscatter or interferometric radar can be used to provide high-resolution data on elevation and topography. Unlike passive sensors, radar can penetrate cloud cover, providing imagery both day and night regardless of weather conditions. The Shuttle Radar Topography Mission (SRTM) provides 30–90 m resolution data on elevation and topography that has been used in species and diversity models. Radar backscatter from QSCAT, Radarsat-1 and SIR-C has been used in land-cover classification and diversity models.

III Measuring species and land-cover classifications

1 Species mapping

Early studies of species mapping used large-scale aerial photography to identify individual plants, especially trees, to species. However, there is an increasing desire to identify and map species within landscapes from high-resolution spaceborne sensors that have been launched in recent years (Sanchez-Azofelfa *et al*., 2003; Turner *et al*., 2003; Goodwin *et al*., 2005). From fine spatial resolution imagery it has been possible to accurately identify some plant species (Martin *et al*., 1998; Haara and Haarala, 2002; Carleer and Wolff, 2004; Foody *et al*., 2005). Much progress has been made in identifying single species of plants, such as non-natives, that are of particular interest in natural resource management. QuickBird was used to map giant reed (*Arundo donax*) in southern Texas with 86–100% accuracy (Everitt *et al*., 2006). The spaceborne hyperspectral sensor Hyperion has shown potential for identifying the occurrence of select invasive species in the southeastern United States, such as Chinese tallow (*Triadica sebifera*), to within 78% accuracy due to distinct leaf phenology (Ramsey *et al*., 2005). There has also been significant progress in identifying tree canopies within forest ecosystems. For instance, high-resolution data has been used to identify mangrove species (Dahdouh-Guebas *et al*., 2004; Wang *et al*., 2004) and seven species of tree were classified with an overall accuracy of 86% in temperate forests in Belgium (Carleer and Wolff, 2004).

Fine spatial resolution imagery (QuickBird, IKONOS, OrbView) from space has also allowed researchers to address questions that previously were impractical to study from space or on the ground. It is now possible, for instance, for studies to be undertaken at the scale of individual tree crowns over large areas (Hurtt *et al*., 2003; Clark *et al*., 2004b). Such data have been used to quantify tree mortality in a tropical rainforest (Clark *et al*., 2004a) and so may contribute usefully to contentious debates on the issue. Moreover, it may sometimes be possible to achieve high levels of accuracy for some species from satellite as well as airborne sensor data (Carleer and Wolff, 2004). There is great potential manually or digitally to identify tree species and canopy attributes from high-resolution imagery. High-resolution imagery is collected primarily from commercial satellites that are still expensive to acquire (US$3000–5000 for 10 km^2). However, the cost should decrease with the competition and an increasing number of archived images. Thus, it should be possible in the near future to identify and map temperate trees to a high degree of accuracy within a landscape and selected tree canopies within stands of tropical forest.

The identification of animals from space is currently difficult because most of the Earth's species are smaller than the largest pixel of current public access satellites (0.6 m) and revisit times are too infrequent for meaningful comparisons. However, measurement of species movements has become commonplace with the advent of the ARGOS satellite tracking system (Gillespie, 2001). This tracking system uses polar orbiting satellites and transmitters that are as small as 5 cm and weigh 49 g to provide location data on the movement of species for over 500 days (Hawkes *et al.*, 2007; Argos, 2008). It has been used to track the movements of thousands of individual animals. Between 2001 and 2007, over 70 peer-reviewed publications used this remote sensing tracking technology to improve our knowledge of biogeography (Argos, 2008). Most terrestrial animal research has been undertaken on raptors (ie, Steppe eagles) and large mammals (ie, Mongolian gazelles) in regions where it is difficult to track their movements in the field (Meyburg *et al.*, 2003; Ito *et al.*, 2005). There have also been rapid advances in the study of marine mammals (West Indian manatees) and reptiles (sea turtles) that are nearly impossible to track in the field (Deutsch *et al.*, 2003; Ferraroli *et al.*, 2004; Hawkes *et al.*, 2007) (Figure 1). As the costs and transmitters' size continue to decrease, this technology will become more available and there is still great potential to identify processes associated with species movements by combining remote sensing data.

2 Land-cover classification

The production of thematic maps of species assemblages is one of the most common applications of spaceborne remote sensing (Foody, 2002). In particular, plant species assemblages and distributional patterns within the landscapes, regions, and continents have long been of interest to biogeographers (von

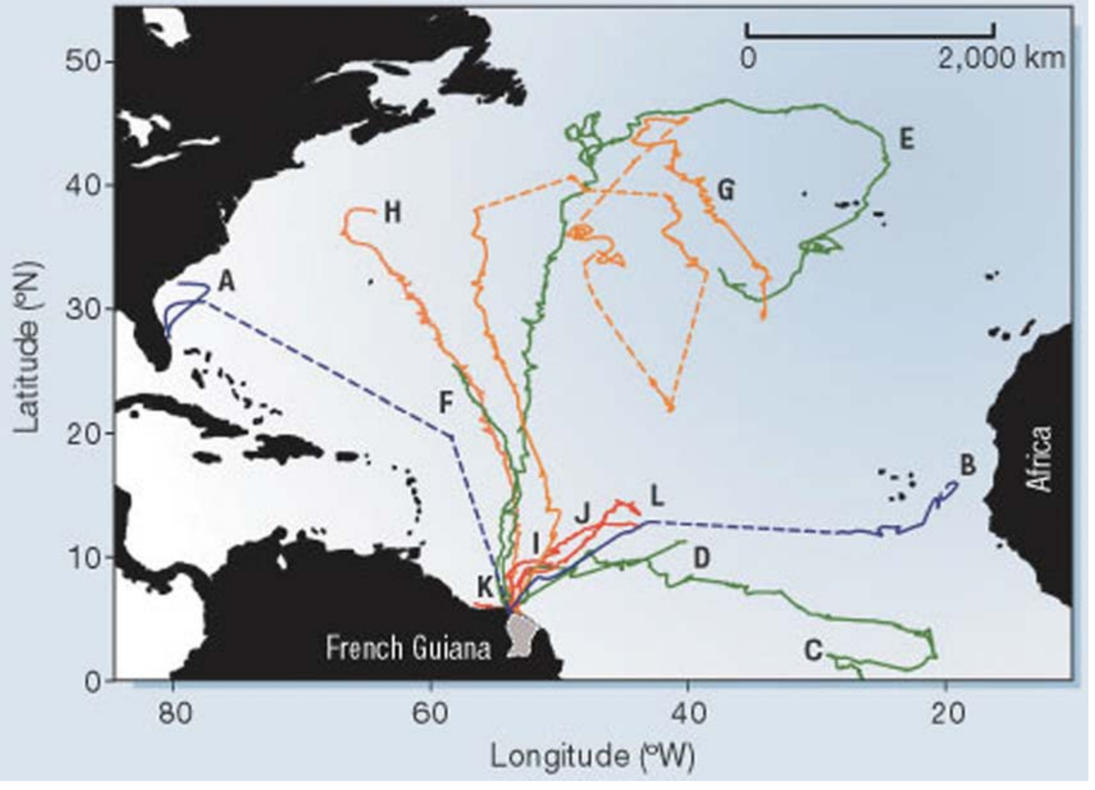

Figure 1 Reconstructed movements of 12 leatherback turtles (A–L) nesting in French Guiana and Suriname

Source: Ferraroli *et al*. (2004).

Humbolt and Bonpland, 1805). Numerous large-area, multi-image-based, multiple-sensor land-cover mapping programmes exist that have resulted in robust and repeatable large-area land-cover classifications (Franklin and Wulder, 2002; Duro *et al*., 2007). Franklin and Wulder (2002) undertook an excellent review of large-scale land-cover classifications, such as CORINE and GAP, that generally seek to attain 85% accuracy across all mapping classes using a variety of passive sensors (TM, SPOT, AVHRR, MODIS) and to a lesser extent active sensors (RADARSAT, JERS). These land-cover classifications provide direct measurements on the distribution of species assemblages. Recently, there have been a number of advances in methods that can improve the resolution and accuracy of land-cover classification. Increased integration of radar data may significantly improve classification accuracy (Saatchi *et al*., 2001; Boyd and Danson, 2005; Li and Chen, 2005). There have also been increased use of new classification techniques such as decision tree- and support vector machine-based approaches and the use of multilayer perception and radial basis function neutral networks that significantly improve accuracy (Foody, 2004a; Boyd *et al*., 2006).

There is a need for further research on information extraction techniques. This includes continued development of image classifiers for the derivation of accurate thematic maps. Contemporary approaches, such as those based on support vector machines (Pal and Mather, 2005) appear to offer many attractions, especially if resources for training the classifier are limited (Foody *et al*., 2006). Attention is also needed on methodological issues such as accuracy assessment, a topic recognized as a major priority area for research (Rindfuss *et al*., 2004). The validity of the maps derived from remote sensing is a critical issue but is fraught with difficulty (Foody, 2002). Critically, however, the required level of accuracy should be defined for an application because in some instances the information provided may be more accurate than suggested in the map's summary accuracy statement (DeFries and Los, 1999) and some applications may require quite modest levels of accuracy (Foody, 2008). There is also much to be gained by moving away from conventional thematic mapping practices. For example, one great advantage of remote sensing is that the analysts can define and map the classes of interest to the application in hand. There is, therefore, no need to be constrained by the map legends. Similarly, there is no need to be constrained to follow the standard image processing approaches to mapping. Finally, there is considerable scope for different types of classification analysis for mapping. In particular, soft or fuzzy classifications have considerable potential. These allow the study of environmental gradients and transition zones and subpixel land cover (Foody, 1996; Rocchini and Ricotta, 2007). In addition, the use of soft classifications in post-classification change detection allows the study of land-cover modifications as well as conversions (Foody, 2001). This is particularly valuable, as remote sensing has focused on conversions, with little attention paid to the severity of change limiting environmental applications (Nepstad *et al*., 1999; Foody, 2001).

IV Modelling biodiversity

1 Species distribution modelling

Species distribution modelling, also known as ecological niche modelling, has been growing at a striking rate in the last 20 years (Guisan and Thuiller, 2005). Species distribution models are based on presence, absence, or abundance data from museum vouchers or field surveys and environmental predictors to create probability models of species distributions within landscapes, regions, and continents (Guisan and Thuiller, 2005). A review of 60 publications between 2001 and 2007 showed a majority developed and explained an approach or technique, evaluated an approach or compared modelling approaches (ie, Maxent versus GARP), or developed new ideas to improve the existing models. Most environmental predictors used in these species distribution models have been based on geographical information system data over different scales (Figure 2). However, there has been an increase in the incorporation of spaceborne remote sensing data on climate, topography, and land cover that has great potential to improve models of species over different spatial scales (Turner *et al*., 2003).

Climatic variables using geographical information system data sets (ie, WorldClim, BIOCLIM) are the primary environmental variables used in species distribution models, especially for regions and continents (Elith *et al*., 2006; Pearson *et al*., 2007). However, recently remote sensing data on precipitation at 0.1 degree from NOAA satellites (Pearson *et al*., 2007) and 0.25 degrees from Tropical Rainfall Mapping Mission (Saatchi *et al*., 2008) have been used in conjunction with ground-based measurements. This may be superior to traditional GIS estimates of precipitation based on interpolation among widely dispersed climate stations in isolated regions. Topography data has also been an important component of species distribution models (Pearson *et al*., 2004; Eltih *et al*., 2006). Topography data is usually collected from digitized elevation maps, but 90 m elevation and topography data are available at a near global extent due to the Shuttle Radar Topography Mission. This data is increasingly being used in species distribution models, especially in the tropics (Chaves *et al*., 2007; Buermann *et al*., 2008; Saatchi *et al*., 2008). Land-cover classifications collected from spaceborne sensors have long been used to link species distributions with vegetation types and associated habitat preference (Nagendra, 2001; Gottschalk *et al*., 2005; Leyequien *et al*., 2007). The greatest accuracy was found with non-mobile species such as plants (Pearson *et al*., 2004). However, vegetation maps as a surrogate for habitat preference have provided insights into the distributions of birds (Peterson *et al*., 2006), herpetofauna (Raxworthy *et al*., 2003), and insects (Luoto *et al*., 2002).

Although the inclusion of suggested remote sensing indices or metrics can offer a great amount of data to improve ecological studies, very few publications used remote sensing data (Turner *et al*., 2003; Pearson *et al*., 2004). Recently, there has been an increase in the utility of spaceborne passive sensors data such as leaf area index (Chaves *et al*., 2007) and percentage tree cover (Buermann *et al*., 2008) for species distribution models (Figure 3). Active airborne sensors such as airborne lidar have been used to improve species distribution models by quantifying vegetation structure within a landscape (Goetz *et al*., 2007). However, a number of recent studies have used radar backscatter from QSCAT (Buermann *et al*., 2008; Saatchi *et al*., 2008) and SIR (Bergen *et al*., 2007) to improve species distribution models

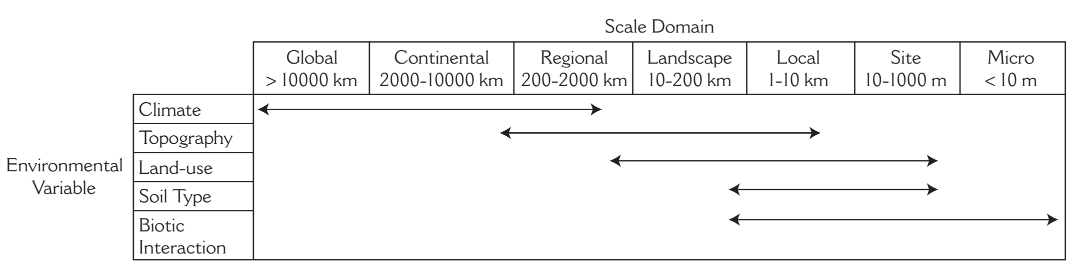

Figure 2 Modelling and environmental variables by spatial scale

Source: Pearson and Dawson (2003).

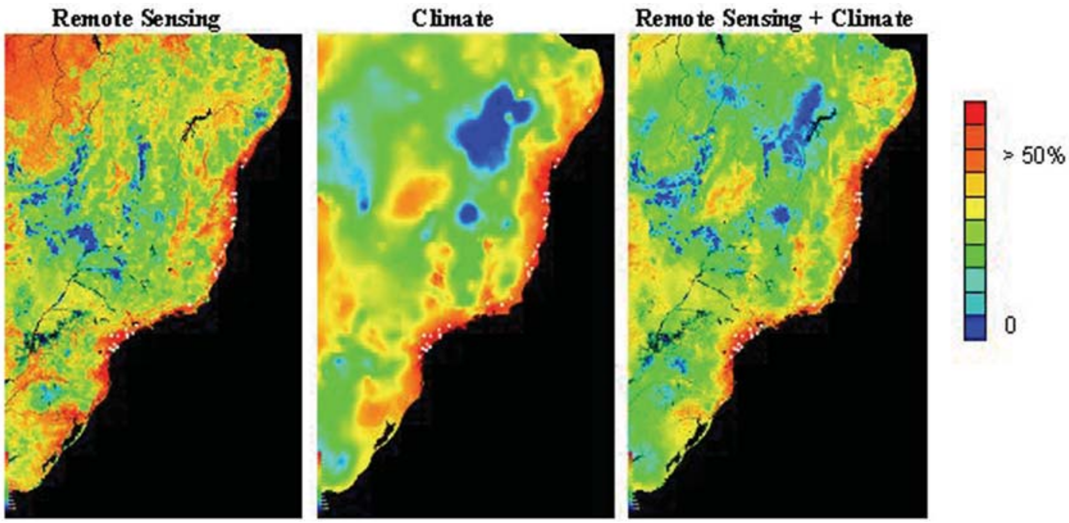

Figure 3 Maxent model of *Carpornis melanocephala* (Black-Headed Berryeater) in Brazil using remote sensing data, climate data, and a combination of both remote sensing and climate data

by providing information on vegetation structure. In the future, remote sensing data and their derived indices should receive increasing attention from researchers applying species distribution modelling techniques. The inclusion of multiscale remote sensing data should allow researchers to improve predictions over different scales, especially at the landscape and regional scales.

2 Diversity models

There have been a number of advances in modelling or predicting species richness, alpha diversity and beta diversity using multisensors that examine relationships over different temporal and spatial scales with increasingly sophisticated methods to improve accuracy. The simplest measure of diversity is species richness or the number of species per unit area (ie, trees per hectare, birds per km^2). The term diversity is more complex and technically refers to a combination of species richness and weighted abundance or evenness data and is generally quantified as an index (Simpson index, Shannon index or Fisher alpha). These indices are used to define alpha diversity, which is the species diversity in one area, community, or ecosystem. Beta diversity refers to the amount of turnover in species composition from one site to another or identifies taxa unique to each area, community, or ecosystem. Beta diversity is more closely related to changes in species similarity or turnover with space. Typically, studies have focused on assessments of species richness with limited attention to other aspects such as species abundance and composition that are difficult to detect from spaceborne sensors (Foody and Cutler, 2003; Schmidtlein and Sassin, 2004). Information on species richness or diversity may be extracted from remotely sensed data in a variety of ways such as land-cover classifications, measures of productivity, and measures of heterogeneity (Nagendra, 2001; Kerr and Ostrovsky, 2003; Leyequien *et al*., 2007).

Many studies have related species richness or diversity to information on the land-cover mosaic of test sites derived from satellite imagery (Nagendra and Gadgil, 1999a; 1999b; Gould, 2000; Griffiths *et al*., 2000;

Kerr *et al*., 2001; Oindo *et al*., 2003; Gottschalk *et al*., 2005; Leyequien *et al*., 2007). Through relationships with land-cover and habitat suitability, it is possible to assess the diversity of species and assess impacts associated with changes in the habitat mosaic such as fragmentation based on landscape metrics (ie, area and isolation) (Kerr *et al*., 2001; *Luoto et al*., 2002; 2004; Cohen and Goward, 2004; Fuller *et al*., 2007; Lassau and Hochuli, 2007). With such indirect approaches to biodiversity assessment, spatial resolution still has an influence on a study as it impacts land-cover classification accuracy and indices of landscape pattern (Foody, 2002; Millington *et al*., 2003; Saura, 2004) as well as the estimation of summary indices of biodiversity and estimates of composition (Kerr *et al*., 2001; Oindo *et al*., 2003). Nonetheless, even with relatively coarse spatial resolution imagery it is possible to derive useful information on diversity (Kerr *et al*., 2001; Foody and Cutler, 2003; Foody, 2004b; Cohen and Goward, 2004).

Alternatively, a direct relationship between measures of species richness and diversity with remotely sensed data has been sought. Most attention has focused on the use of the popular normalized difference vegetation index (NDVI) from passive sensors because it is easy to calculate using the red and near infrared bands common to almost all passive spaceborne sensors (Oindo and Skidmore, 2002; Seto *et al*., 2004; Gillespie, 2005; Lassau and Hochuli, 2007). NDVI has been associated with net primary productivity and has been hypothesized to quantify species richness and diversity based on the species-energy theory (Currie, 1991; Evans *et al*., 2005). An increasing number of studies and reviews have found significant associations between NDVI and diversity (Nagendra, 2001; Kerr and Ostrovsky, 2003; Leyequien *et al*., 2007). Many studies have reported significant positive correlations between plant species richness or diversity from plot or regions data and NDVI in both temperate (Fairbanks and McGwire, 2004; Levin *et al*., 2007; Rocchini, 2007a) and tropical ecosystems (Bawa *et al*., 2002; Gillespie, 2005; Feeley *et al*., 2005; Cayuela *et al*., 2006) (Figure 4). NDVI can explain between

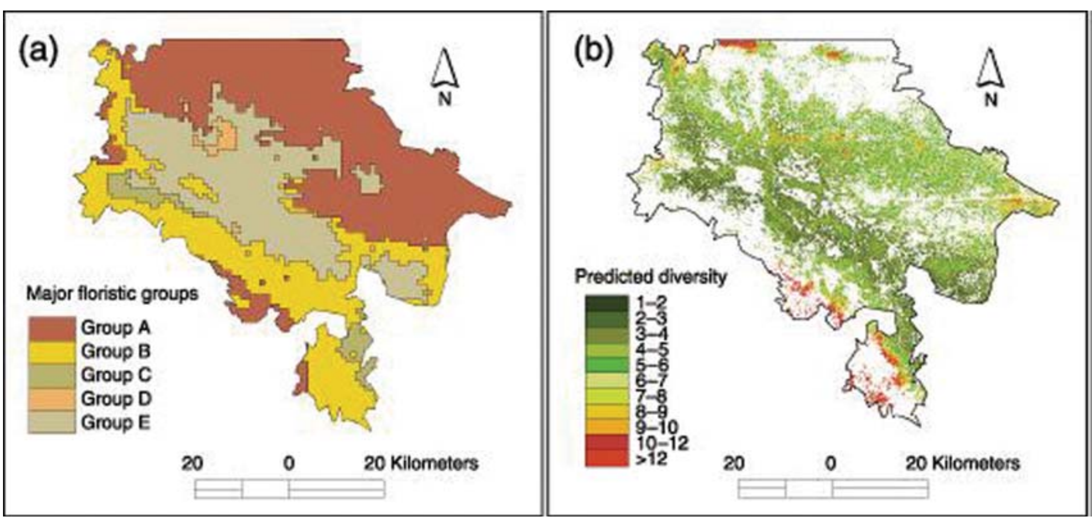

Figure 4 Predicted values of á tree diversity (Fisher's alpha) in the Highlands of Chiapas, Mexico, and prioritization of areas for conservation based on identification of high predicted á tree diversity within each floristic region

Source: Cayuela *et al*. (2006).

30% and 87% of the variation in species richness or diversity within a vegetation type, landscape, or region. Results for terrestrial fauna are more complicated given the mobility of faunal species and because NDVI does not directly quantify animal species but species habitats (Leyequien *et al*., 2007). Similar relationships between NDVI and diversity have been noted for animal taxa such as birds and butterflies within landscapes (Seto *et al*., 2004; Goetz *et al*., 2007) and regions (Hurlbert and Haskell, 2003; Foody, 2004b; Ding *et al*., 2006; Bino *et al*., 2008). However, NDVI does not always have a positive relationship with animal species richness and there is no consensus as to which scale results in the greatest accuracy.

Heterogeneity in land-cover types, spectral indices, and spectral variability derived from satellite imagery has also been correlated with species richness (Gould, 2000; Rocchini, 2007b). This is largely based on the hypothesis that heterogeneity in land cover, spectral indices, or spectral variability within an area or landscape is an indicator of habitat heterogeneity which allows more species to coexist and hence greater species richness (Simpson, 1949; Palmer *et al*., 2002; Carlson *et al*., 2007; Rocchini *et al*., 2007). The variation in land-cover types within an area has been associated with species richness for a number of taxa (Gould, 2000; Kerr *et al*., 2001; Leyequien *et al*., 2007). Variation in spectral indices has been shown to be positively associated with species richness and diversity for a number of taxa in different regions (Gould, 2000; Oindo and Skidmore, 2002; Fairbanks and McGwire, 2004; Levin *et al*., 2007). More advanced techniques have examined the variability of spectral signals in satellite imagery which has been demonstrated to have an intrinsic power in evaluating species diversity (ie, Spectral Variation Hypothesis; Palmer *et al*., 2002), since it is expected that the higher the spectral variability is, the higher the habitat and species variability will be (Carlson *et al*., 2007; Rocchini *et al*., 2007).

While knowledge of species richness and alpha diversity represents crucial components in diversity studies, the concept of beta diversity (ie, the amount of species turnover) is also important since it adds to the simpler concept of alpha diversity the capability of detecting spatial gradients that functionally act in determining the spatial variation in species composition (Koleff *et al*., 2003; Nekola and Brown, 2007). To date, few efforts have been made to relate species turnover to spectral variability, substantially confining spectral variation hypothesis to species richness prediction (Chust *et al*., 2006; Cayuela *et al*., 2006). Tuomisto *et al*. (2003) and Rocchini (2007a) built distance decay models replacing spatial distance by spectral ones, on the strength of the expected high species turnover at high ecological and thus spectral distance. Rocchini *et al*. (2005) derived species accumulation curves by ordering plots according to their maximum spectral distance, thus accumulating a higher number of species than random curves given the same sampling effort (Figure 5) and promoting spectral

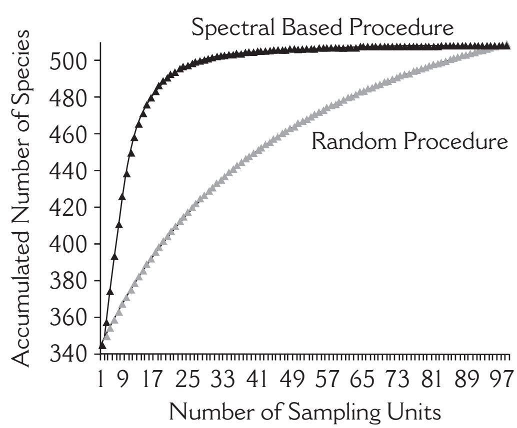

Figure 5 Species accumulation curves. Ordering plots on the strength of their maximum spectral distance should result in a higher number of species than random curves, thus promoting spectral variability as a straightforward tool for inventorying species in a lower timelag

variability as a straightforward tool for inventorying species in a lower timelag. Both examples demonstrated the powerfulness of using spectral distance between sites for beta diversity estimates and species inventory maximization.

Most recently, there has been a move towards the use of multiple remote sensing sensors over different time periods and increasingly sophisticated approaches to modelling diversity over different spatial scales. Many remote sensing studies of diversity to date have employed the use of one sensor at one period in time (ie, Gillespie, 2005; Feeley *et al*., 2005; Gottschalk *et al*., 2005). However, increasingly diversity studies are undertaken using multiple passive sensors (ie, Landsat, ASTER, QuickBird) (Levin *et al*., 2007; Rocchini, 2007b) or examine relationships with diversity over different time periods (Fairbanks and McGwire, 2004; Foody, 2005; Levin *et al*., 2007; Leyequien *et al*., 2007). These studies are important in the assessment of individual sensors and the effects of seasonality. There has also been an increasing interest in the combination of passive and active sensors to improve species diversity models. Active spaceborne sensors can provide data on the vegetation structure that has been associated with diversity, especially avian diversity, across a number of spatial scales (Imhoff *et al*., 1997; Bergen *et al*., 2007; Goetz *et al*., 2007; Leyequien *et al*., 2007). Recent advances in the modelling of species diversity with a combination of passive sensors (MODIS) and active sensors (QSCAT, SRTM) from satellites has also been used to model tree diversity for the entire Amazon Basin (Saatchi *et al*., 2008).

There has also been an increase in sophisticated statistical and spatial analyses to study diversity. The prediction of diversity has substantially relied on simple univariate regression or multiple regression models appropriately scaling sensor imagery to field data on vascular plants (Gould, 2000; Fairbanks and McGwire, 2004; Carter *et al*., 2005; Rocchini, 2007b; Levin *et al*., 2007), lichens (Waser *et al*., 2004), and mammals (Oindo and Skidmore, 2002). While these approaches provide a basic understanding of patterns and can be used to create predictive diversity maps for a landscape, region, or continent, more sophisticated techniques are being examined and developed to model patterns of diversity (Foody, 2004a; 2005). General linear models and general additive models have become increasingly important in the spatial prediction of biodiversity patterns; however, they have been poorly used considering remote sensing data (Luoto *et al*., 2002; Schwarz and Zimmermann, 2005). Spatial statistics such as geographically weighted regression analyses have also resulted in improved models of diversity (Foody, 2005). Furthermore, increased accuracy of predictions can be obtained using more complex approaches such as neural networks (Foody and Cutler, 2006).

Finally, the effects of scale have long been recognized as needing to be accounted for in biodiversity studies, but this remains a major challenge (Whittaker *et al*., 2001; Willis and Whittaker, 2002). Given the importance of the spatial dimension to biogeographical research (Millington *et al*., 2003) such scale-related issues are likely to be a major component of future research especially for biogeographers interested in creating predictive diversity maps. While the ability to provide complete data coverage for large areas is often seen as a major advantage of remote sensing, some problems of working with large areas have not been addressed. It is generally assumed that relationships between the biodiversity variable of interest and the remotely sensed response are spatially stationary and hence transferable between sites within the region of study. The spatial resolution and scale dependence of relationships noted in the literature, however, indicate that the relationships assessed may be spatially non-stationary (Foody, 2004b). The commonly made assumption that relationships will remain spatially stationary may be untenable and have a negative impact on the generalizabilty of remote sensing methods. Various methods may be used to model non-stationary relationships and have been applied in the modelling of wildlife distributions from remote sensing (Foody, 2005; Osborne *et al.*, 2007). Critically, however, remote sensing offers the ability to obtain multiscale observations and data to explore non-stationary relationships.

V Conservation planning

It is well established that biodiversity is threatened greatly by human activity (Myers *et al.*, 2000). In particular, land-cover changes such as those linked to human-induced habitat loss, fragmentation, and degradation represent the largest current threat to biodiversity (Chapin *et al.*, 2000; Menon *et al.*, 2001; Gaston, 2005). Remote sensing can be used to derive information on fragmentation, often in the form of landscape pattern and shape indices calculated from a thematic map produced with an image classification analysis (Gillespie, 2005; Lung and Schaab, 2006). Although valuable, the approach clearly requires an accurate classification and the relationship between classification accuracy and landscape pattern index accuracy is not necessarily a simple one (Foody, 2002; Langford *et al.*, 2006). However, it is possible to tailor the process to suit the circumstances of a particular conservation application such as certain land-cover types. It is possible to focus attention on just these classes, saving time, effort and resources that would otherwise be directed on the classes of no interest. This is often valuable in resource-limited conservation applications. As an example, the European Union's Habitats Directive seeks to maintain the extent of valuable habitats on a no-net-loss policy. Remote sensing may be used to monitor a habitat of interest with a one-class classification approach adopted to focus effort and resources on the class of interest (Boyd *et al.*, 2006; Sanchez-Hernandez *et al.*, 2007). This can also reduce problems associated with not satisfying the assumptions of an exhaustively defined set of classes that is commonly made in a standard classification analysis (Foody, 2004a).

In recognition of the need to conserve biodiversity, reserves and other such protected areas have been formed. Remote sensing may have a major role to play in helping to prioritize candidate locations for new reserves (Schulman *et al.*, 2007a). The conservation of biodiversity needs accurate and up-to-date information (Knudby *et al.*, 2007). Methods to identify priority areas for conservation have generally focused on biological variables (Shi *et al.*, 2005) and often only relatively coarse biological information is needed to identify priorities for conservation (Harris *et al.*, 2005). Frequently, what is required in conservation assessments is a quick but rigorous method to identify where human-induced threats and high biodiversity coincide (Ricketts and Imhoff, 2003). Remote sensing offers a repeatable, systematic, and spatially exhaustive source of information on key variables such as productivity, disturbance, and land cover that impact biodiversity (Duro *et al.*, 2007; Wright *et al.*, 2007). Moreover, the provision of data for large areas is especially attractive in remote and often inaccessible regions (Cayuela *et al.*, 2006; Saatchi *et al.*, 2008). As such, remote sensing is often a cost-effective data source (Luoto *et al.*, 2004) and enables rapid biodiversity assessments (Lassau and Hochuli, 2007).

Remote sensing may also be valuable after the establishment of reserves, not least because competing pressures, such as those associated with economic development and population growth, place great stress on reserves and the surrounding lands (Nagendra *et al.*, 2004). The spatial coverage provided by remote sensing offers, however, the potential to monitor the effectiveness of protected areas, allowing comparisons of changes inside and outside of reserves to be evaluated (Southworth *et al.*, 2006; Wright *et al.*, 2007). The ability to monitor the areas outside formally protected reserves is also attractive as these may have a major role to play in conserving biodiversity (Putz *et al.*, 2001). For example, even relatively severely logged forest outside a reserve may represent a significant resource for biodiversity conservation (Cannon *et al.*, 1998) and secondary forests are an often overlooked resource that may be managed to help reduce pressures elsewhere (Bawa and Seidler, 1998). Thus, actions inside and outside the protected areas are important, supporting the view that biodiversity conservation activities should be undertaken at the level or scale of the landscape (Nagendra and Gadgil, 1999b; Margules and Pressey, 2000; Potvin *et al.*, 2000; Hannah *et al.*, 2002). This activity may benefit from remote sensing as its synoptic overview provides information on the entire landscape.

Remote sensing may be a useful component to general biodiversity assessments, especially in providing data at appropriate spatial and temporal scales. For example, the biodiversity intactness index was proposed recently as a general indicator of the overall state of biodiversity to aid monitoring and decision-making (Scholes and Biggs, 2005). Although there are concerns for its use, notably with the impacts of land degradation, remote sensing may be an important source of data for its derivation (Rouget *et al.*, 2006).

VI Conclusions

There can be no question that spaceborne imagery has made significant contributions to the science of biogeography and biodiversity over the last seven years. Future research should focus on incorporating recent and new spaceborne sensors, more extensive integration of available data from passive and active imagery that can be used across spatial scales, and the collection and dissemination of high-quality field data.

The recent developments in satellite and sensor technology will further improve our abilities directly and indirectly to study biogeographical patterns of biodiversity from space. The increase in high-resolution spectral satellites will make it possible to acquire data at enhanced spatial (1 m), spectral (visible, infrared, thermal), and radiometric resolutions (11 bit) that can be used to map individual species. Indeed, Google Earth has led the way by providing QuickBird imagery (Loarie *et al.*, 2008). Future, radar satellites may be ideal for studying species distributions and diversity patterns, especially in regions with high cloud cover like the tropics. There will be ten satellites (SAR-Lupe, COSMO- SkyMed, TerraSAR-X) launched by 2009 that provide elevation and radar backscatter data to 1 m pixel resolution (Gillespie *et al.*, 2007). This will provide valuable multidimensional data sets (vegetation structure, biomass, land-cover classifications) that should result in a richer characterization of the environment than conventional passive image data sets.

The full information content of existing data sets is often not used in biodiversity studies. There should perhaps be a move away from analyses based upon simple summary indices that commonly underuse spectral regions and are undertaken at a single spatial scale (Asner *et al.*, 2004). Biogeographers are perfectly positioned to take advantage of the different satellite data sets that integrate climate, topography, spectral, and radar data over a landscape, regional, continental, and global spatial scale. This would allow an increased understanding of species distributions, land-cover classifications, diversity models, and near real-time conservation planning data across multi-spatial scales.

Finally, even if satellite imagery has been enthusiastically advocated as the resource of the future for directly and indirectly investigating biodiversity from space, it is worth remembering that it should aim at sustaining rather than replacing field-based methodologies. Biogeographers should continue to collect and share high-quality data on plants and animals including high-resolution location data that can be used in the future to test or validate models. There should be an increasing number of data sets such as Synthesis and Analysis of Local Vegetation Inventories Across Scales (SALVIAS) where scientists can store and share data with the scientific community.

For these reasons, it appears that biogeography as a discipline has a secure place in science and should continue to improve our understanding of the distributions of life on earth.

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