Remote sensing for biodiversity science and conservation

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Remote-sensing systems typically produce imagery that averages information over tens or even hundreds of square meters – far too coarse to detect most organisms – so the remote sensing of biodiversity would appear to be a fool's errand. However, advances in the spatial and spectral resolutions of sensors now available to ecologists are making the direct remote sensing of certain aspects of biodiversity increasingly feasible; for example, distinguishing species assemblages or even identifying species of individual trees. In cases where direct detection of individual organisms or assemblages is still beyond our grasp, indirect approaches offer valuable information about diversity patterns. Such approaches derive meaningful environmental parameters from biophysical characteristics that are revealed by remote sensing.

Since the days of Darwin and Wallace, ecologists and evolutionary biologists have sought to explain the distribution of species or groups of species, and to discover why certain places are especially rich in species. Today, conservation biologists rely on estimates of species richness (i.e. the number of species in a particular place) as they race to determine areas in which to spend limited resources in an age of rapid biodiversity decline. Scientifically sound environmental management requires frequent and spatially detailed assessments of species numbers and distributions. Such information can be prohibitively expensive to collect directly. Measuring the distribution and status of biodiversity remotely, with airborne or satellite sensors, would seem an ideal way to gather these crucial data. But can remote sensing (Box 1) become an effective tool for exploring patterns of biodiversity? Can we detect individual species or species assemblages from afar or measure the environmental parameters that are necessary to estimate the distributions of species, levels of species richness, or the structure of ecological communities?

The potential for modern sensors to identify areas of significance to biodiversity, predict species distributions and model community responses to environmental and anthropogenic changes is an important research topic. Underlying this effort is the assumption that certain key environmental parameters, with remotely detectable biophysical properties, drive the distribution and abundance of species across landscapes and determine how they occupy habitats. New imagery and data sets are now enabling remote sensing, in conjunction with ecological models, to shed more light on some of the fundamental questions regarding biodiversity. These tools should prove useful to those seeking to generate basic knowledge about why organisms are found where they are, as well as those asking the more applied question of where to invest conservation funds.

Here, we use the term 'biodiversity' in its organismal sense to refer to species and certain characteristics of species, in particular their distribution and number within a given area. We also use 'biodiversity' more broadly to mean species assemblages and ecological communities (i.e. groups of interacting and interdependent species). There are two general approaches to the remote sensing of biodiversity. One is the direct remote sensing of individual organisms, species assemblages, or ecological communities from airborne or satellite sensors. New spaceborne systems with very high spatial (also known as hyperspatial) resolutions are now available from commercial sources. For the first time, the direct remote sensing of certain large organisms and many communities is possible with unclassified satellite imagery. Likewise, new hyperspectral sensors slice the electromagnetic spectrum into many more discrete spectral bands, enabling the detection of spectral signatures that are characteristic of certain plant species or communities.

The other approach is the indirect remote sensing of biodiversity through reliance on environmental parameters as proxies. For example, many species are restricted to discrete habitats, such as a woodland, grassland, or seagrass beds that can be clearly identified remotely. By combining information about the known habitat requirements of species with maps of land cover derived from satellite imagery, precise estimates of potential species ranges and patterns of species richness are possible. Just such an approach has been employed extensively in the US GAP analysis program [1]. Of course, it is probable that no single environmental parameter drives patterns of species distribution and richness. Many possible drivers have been

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http://tree.trends.com 0169-5347/03/$ - see front matter. Published by Elsevier Science Ltd. doi:10.1016/S0169-5347(03)00070-3

Box 1. Introduction to remote sensing

Here, 'remote sensing' refers to the detection of electromagnetic energy from aircraft or satellites. The electromagnetic spectrum can be divided into wavelength regions known as 'optical' and 'microwave'. Optical remote sensing targets energy reflected and emitted by the Earth, typically at wavelengths between 0.4 and 14 μm. Microwave remote sensing detects much longer wavelengths, between ~1 mm and 1 m. Optical and microwave radiation occupy distinct regions of the electromagnetic spectrum and are detected using distinct technologies (Fig. I).

The two principal types of sensor discussed here are 'passive' and 'active'. Passive sensors measure radiation that reaches a detector without the sensor first transmitting a pulse of radiation. Active sensors emit a pulse and later measure the energy returned or bounced back to a detector. Both passive and active sensors record the intensity of a signal within a wavelength interval, known as a 'band' or 'channel', of specified width within the electromagnetic spectrum.

Data are often distributed to remote-sensing practitioners in a matrix of square picture elements (or pixels). The size of these pixels corresponds to the 'spatial resolution' of the sensor, which determines the smallest object detectable. So, '30 m data' would refer to data in a matrix of 30 m × 30 m pixels. The matrix of pixels is often called a 'scene'. Scene sizes also vary; for example, the Enhanced Thematic Mapper + sensor on the Landsat 7 satellite produces scenes that are 183 km wide × 170 km long.

Land-cover and land-use monitoring commonly use passive sensors to measure visible, near- and middle-infrared, and thermal-infrared radiation. Data describing energy reflected or emitted from the surface of the Earth are statistically or visually analyzed to identify objects.

Vegetation structure and ground surface elevations are often measured using active sensors. Light detection and ranging (lidar) systems operate in visible to near-infrared wavelengths, while radio detection and ranging (radar) emits radiation in longer microwave wavelengths [33]. Characteristics of the energy pulses influence the strength and likelihood of returned signals. Both the strength and timing of the returned signal describe physical properties of remotely sensed objects.

The width of the bands of the electromagnetic spectrum detected by a sensor determine its ability to detect spectral differences and as such constitute the spectral resolution of that instrument. All objects have a spectral signature based upon how they reflect and emit electromagnetic radiation. More spectral bands of narrower width allow researchers to find more unique features within the spectral signature of an object that distinguish it from other objects.

Temporal resolution, or 'revisit time', refers to the time period between repeat passes over an object being remotely sensed. For example, Landsat satellites pass over the same point on the surface of the Earth every 16 days. Thus, they have a 16-day revisit or repeat time. Systems that image wider areas might pass over the same point every day but must usually sacrifice spatial resolution to do so (i.e. they can only detect much larger objects). Temporal resolution is especially important when one is trying to obtain a clear view of areas frequently obscured by clouds (or other atmospheric phenomena) because optical sensors cannot view through clouds.

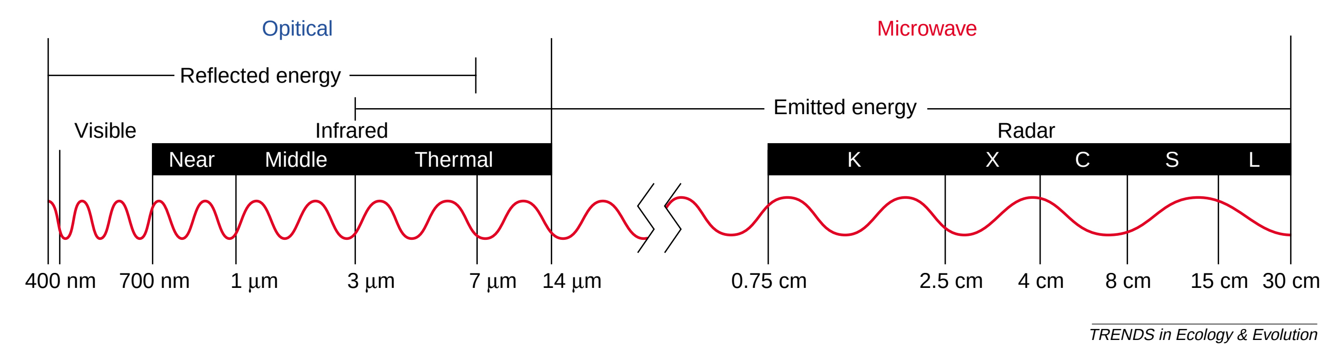

Fig. I.

proposed (Table 1). Here, we focus on three often-cited environmental parameters that now lend themselves particularly well to detection because of recent advances in remote-sensing technology: primary productivity, climate and habitat structure (including topography) [2–5].

For the conservation biologist, remotely sensed imagery exposes land-cover changes at spatial scales from local to continental, letting one monitor the pace of habitat loss and conversion [6,7]. These measurements of habitat loss can be converted into quantitative estimates of biodiversity loss through the use of the species–area relationship (Box 2), which underlies many current estimates of biodiversity decline [8–12]. Remote sensing provides the area component of the equation. Public and nongovernmental conservation

Box 2. Species–area relationship

The species–area relationship is one of the oldest rules of ecology. Naturalists of the 19th century recognized that the number of species in an area is a function of the size of the area, and Arrhenius [34] showed that the relationship could be described with a power function: $S = cA^z$ where S is the number of species, A is area, and c and z are constants. Work by Preston [35] and MacArthur and Wilson [36] later helped to square this relationship with ecological theories about the relative abundances of species within communities and the numbers of species found on islands. More recent work by Rosenzweig [3] and others has led to a more subtle understanding of the effect of scale on the species–area relationship.

Using the species–area relationship, conservation biologists have derived estimations of the proportion of species lost as a result of habitat loss, according to the formula: $S_{new}/S_{original} = (A_{new}/A_{original})^z$ (see [8]). The key element in this process is estimating the proportion of habitat loss, which is where remote sensing has become increasingly useful. New data sets on the pace and pattern of deforestation produced by satellite-based sensors are becoming available at global to local scales [7,37] and are making remote assessments of species losses possible [38]. By further coupling the species–area relationship and remotely sensed deforestation rates, researchers have projected the impacts of a variety of conservation scenarios in the face of 21st-century deforestation [12].

Table 1. Examples of ecological variables and data sources useful for quantifying and modeling biodiversity[a]

Ecological variable	Sensor[b] Space (S)/ Airborne (A)	Spatial resolution	Revisit time	Spectral resolution	Description	Website
Direct approaches						
Species composition	TM/ETM + (S), ALI (S), HYPERION (S), ASTER (S), IKONOS (S), Quickbird (S), AVIRIS (A), CASI (A)	<1–30 m	16 days (ETM, ALI, Hyperion); 4–16 days (ASTER); 2–5 days (IKONOS); 2–4 days (Quickbird); N/A for aircraft	V/NIR, SWIR, ASTER also has TIR	These sensors are being tested for their ability to measure directly canopy community, and perhaps species, type based upon unique spectral signatures	c–i
Land cover	MODIS (S), TM/ETM + (S), ASTER (S), ALI (S), IKONOS (S), Quickbird (S)	<1–1000 m	1–2 days (MODIS); 16 days (TM/ETM +); 4–16 days (ASTER); 2–5 days (IKONOS); 2–4 days (Quickbird)	V/NIR, SWIR, MODIS and ASTER also have TIR	Can discriminate different land surfaces at various resolutions; land cover classification is considered a first-order analysis for species occurrence	c–e,h,i,k
Indirect approaches						
Primary Productivity						
Chlorophyll	SeaWIFS (S), MODIS (S), ASTER (S), TM/ETM + (S), ALI (S), Hyperion, (S), IKONOS (S), Quickbird (S), AVIRIS (A), CASI (A)	<1–1000 m	1 day (SeaWiFS); 1–2 days (MODIS); 4–16 days (ASTER); 16 days (TM/ETM + , ALI, Hyperion); 2–5 days (IKONOS); 2–4 days (Quickbird); N/A (AVIRIS, CASI)	V/NIR, SWIR, MODIS and ASTER also have TIR	Measure reflectance to assess presence/absence of vegetation and relative greenness measures enabling detection of ocean and land surface chlorophyll useful for calculating productivity and plant health	c,d,f–k
Ocean color and circulation	TOPEX/Poseidon (S), AVHRR (S), MODIS (S), SeaWiFS (S)	1–10 km	10 days (TOPEX/Poseidon); 1 day (AVHRR); 1–2 days (MODIS); 1 day (SeaWIFS)	TOPEX/Poseidon; (microwave) AVHRR, MODIS, SeaWiFS (V/NIR, SWIR, MODIS and AVHRR also have TIR)	Circulation patterns can be inferred from changes in ocean color, sea surface height, and ocean temperature, important for understanding larval transport and movement of pathogens and sediment	j–m
Climate						
Rainfall	CERES (S), AMSR-E (S)	20–56 km	1–2 days (CERES, AMSR-E)	Microwave	Enable detection of precipitation and surface moisture at coarse resolutions; such data parameterize models of species occurrence based on drought tolerance	n,o
Soil moisture	AMSR-E (S)	5.4–56 km	1–2 days	Microwave	Can be estimated over rel. large areas; data parameterize models of species occurrence based on moisture requirements	o
Phenology	MODIS (S), TM/ETM + (S), ASTER (S), ALI (S), HYPERION (S), IKONOS (S), Quickbird (S)	1–1000 m	1–2 days (MODIS); 16 days (TM/ETM + , ALI, Hyperion); 4–16 days (ASTER); 2–5 days (IKONOS); 2–4 days (Quickbird)	V/NIR, SWIR, MODIS and ASTER also have TIR	Information on leaf turnover and flowering/fruiting cycles can be inferred from comparisons of time series of images. Provides for identification of species tied to certain phenological events	c–e,h,i,k
Habitat Structure						
Topography	SRTM (S), ATM (A), ASTER (S), IKONOS (S), SLICER (A), LVIS (A)	90 m SRTM; 30 m/15 m ASTER; 1–15 m IKONOS, SLICER, LVIS	N/A (SRTM); 4–16 days (ASTER); 2–5 days (IKONOS); N/A (SLICER, LVIS)	Microwave SRTM; V/NIR and SWIR for others	Digital elevation models derived from radar signals via interferometry (SRTM); image stereo pairs (ASTER) or discrete-return (usually) LIDAR signals. Many species are constrained by microhabitats resulting from changes in altitude; elevation also determines watershed flows	e,h,p–s

(*continued on next page*)

Table 1 (*continued*)

Ecological variable	Sensor[b]Space (S)/ Airborne (A)	Spatial resolution	Revisit time	Spectral resolution	Description	Website
Vertical canopy structure	SLICER (A), LVIS (A)	1–10 m	N/A (SLICER, LVIS)	V/NIR	Provides 3D measurements via laser pulses; provides biomass estimates and information about vegetation structure	r,s

[a]Abbreviations: ALI, Advanced Land Imager; AMSR-E, Advanced Microwave Radiometer for EOS; ASTER, Advanced Spaceborne Thermal Emission and Reflection Radiometer; ATM, Airborne Topographic Mapper; AVHRR, Advanced Very-High Resolution Radiometer; AVIRIS, Airborne Visible/Infrared Imaging Spectrometer; CASI, Compact Airborne Spectrographic Imager; CERES, Clouds and the Earth's Radiant Energy System; ETM +, Landsat Enhanced Thematic Mapper Plus; LIDAR, Light Detection and Ranging; LVIS, Laser Vegetation Imaging Sensor; MODIS, Moderate-resolution Imaging Spectroradiometer; SeaWiFS, Sea-viewing Wide Field-of-view Sensor; SLICER, Scanning Lidar Imager of Canopies by Echo Recovery; SRTM, Shuttle Radar Topography Mission; SWIR, short-wave infrared (roughly corresponds to the near and middle infrared bands); TIR, thermal infrared; TM, Landsat Thematic Mapper; TOPEX, The Ocean Topography Experiment; V/NIR, visible/near-infrared.
[b]Sensors listed are a sample of relevant sensors and show a bias toward NASA-validated systems because of the experience of the authors.
[c]http://landsat.gsfc.nasa.gov/
[d]http://eo1.gsfc.nasa.gov/
[e]http://asterweb.jpl.nasa.gov/
[f]http://aviris.jpl.nasa.gov/
[g]http://www.itres.com/
[h]http://www.spaceimaging.com/
[i]http://www.digitalglobe.com/
[j]http://seawifs.gsfc.nasa.gov/SEAWIFS.html
[k]http://modis.gsfc.nasa.gov/
[l]http://topex-www.jpl.nasa.gov/
[m]http://www.ngdc.noaa.gov/seg/globsys/avhrr.shtml
[n]http://asd-www.larc.nasa.gov/ceres/ASDceres.html
[o]http://wwwghcc.msfc.nasa.gov/AMSR
[p]http://www.jpl.nasa.gov/srtm/
[q]http://aol.wff.nasa.gov/aoltm.html
[r]http://denali.gsfc.nasa.gov/research/laser/slicer/slicer.html
[s]http://lvis.gsfc.nasa.gov/

organizations worldwide leverage their understanding of species–area relationships with imagery-based habitat classifications to estimate species losses associated with changes in land cover and land use (Box 3). The challenge is to go beyond this approach to a more detailed understanding of which species are being lost and why. How can we match existing and emerging remote-sensing technologies to parameters that have clear implications for organisms and ecosystems?

Here, we review evidence that indicates that we might be close to improving greatly the detection of species, ecological communities and patterns of species richness with remote sensing. We explore recent advances in technology, addressing direct and indirect approaches to the remote sensing of biodiversity. Following the discussion of each technology, we offer examples of applications of that technology to the issue at hand.

Direct remote sensing of species and species assemblages

Hyperspatial technology and its applications

Recently launched commercial satellites with very high spatial resolution, multispectral sensors are improving our ability to resolve objects at spatial scales previously only attainable from aerial photography or classified satellite imagery. The IKONOS system from Space Imaging and the QuickBird system from DigitalGlobe offer multispectral imagery at resolutions of 4 m and 2.4–2.8 m, respectively, and panchromatic imagery at 1 m and 0.6–0.8 m, respectively. At these resolutions, direct identification of certain species (e.g. through the detection of individual tree crowns) and species assemblages is becoming feasible. Remote sensing of phenological change (e.g. fruiting events and early/late onset of greenness or senescence) holds promise as a method for the detection of vegetation types down to the species level. Capturing plant phenology does require a sensor with high temporal resolution (Fig. 1).

Early research into applying IKONOS imagery to find and count baleen whales at or near the ocean surface shows promise, and would provide another tool to those charged with monitoring these and other protected whale species [13]. In a freshwater context, IKONOS imagery has been used in conjunction with Landsat to map the expansion of a non-native invasive plant species [14]. Watershed research in small catchments (<260 ha) requires data sets at spatial resolutions of 30 m or finer (E.P. Gardiner, PhD thesis, University of Georgia 2002).

Hyperspectral technology and its applications

In tandem with increases in spatial resolution, gains in spectral resolution offer new possibilities for the direct remote sensing of biodiversity patterns. Perhaps the best examples of fine-scale, species-specific land-cover classification through spectral analysis come from the use of airborne and spaceborne hyperspectral sensors. These devices differ from multispectral sensors (which detect relatively few discrete bands) in that they detect reflected radiation across a continuous spectrum, often including 200 or more contiguous spectral bands. This added spectral resolving power is useful in sorting out finer differences among traditional land-cover classes, typically based on vegetation and soils. Once atmospheric interference has been accounted for and the information validated, acquired spectral signatures can be compared to spectral libraries, which enable rapid

Box 3. New opportunities with Landsat

Today's researcher has more options than ever in terms of the volume and variety of available remote-sensing imagery. Landsat satellites have provided multispectral imagery products for 30 years, and their long history and reliability have made them a popular source for documenting changes in land cover and use over time. New operating conditions and recent US Government data purchases have greatly increased the availability of this imagery. The 1999 launch of the Landsat 7 satellite marked the return of the Landsat program to US Government operation and resulted in a price reduction to US$600 per scene, down from several thousand dollars. Future reductions are possible as increases in data purchases enable savings in operations costs to be made.

Landsat 7 also provides a higher spatial resolution 15-m panchromatic (i.e. broad-band black and white) band to augment the 30-m resolution of its six visible to middle infrared bands. In addition, more data are available: US Government acquisition plans call for the capture of a nearly global set of images every three to six months. The USA is also investing in the development of historical Landsat global datasets from the mid-1970s (at the coarser 79-m spatial resolution available at that time), *c.* 1990 (at 30-m resolution), and from 2000. These data will be publicly available from the Earth Resources Observation Systems Data Center of the US Geological Survey, and will provide baseline information for analyses of past land cover and the detection of land cover change.

land-cover classification, characterization and change detection.

The Hyperion instrument on the Earth Observing-1 (EO-1) satellite of NASA records visible light and other reflected electromagnetic energy ranging from 0.4 to 2.5 μm in 220 channels that are 10-nm wide. Its spatial resolution of 30 m and the orbit of the satellite complement those of Landsat. Although Hyperion is the first civilian spaceborne hyperspectral sensor, the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) from NASA pioneered hyperspectral research in a variety of applications, including vegetation and mineral classification.

Hyperspectral measures of leaf-surface attributes during different seasons can yield useful information about ecosystem functioning, evolution and change [15]. When analyzed together with remotely derived indices [e.g. leaf-area index (LAI) and the fraction absorbed photosynthetically active radiation (FAPAR)] and then assimilated into models that include edaphic parameters, hyperspectral data offer the potential to observe patterns of species diversity.

One application is the detection and mapping of invasive species. Research conducted in the Theodore Roosevelt National Park of western North Dakota, USA, successfully detected infestations of leafy spurge *Euphorbia esula*, using three hyperspectral sensors at three separate ground spatial resolutions. All three sensors could detect infestations to varying degrees. The Hyperion instrument achieved mapping accuracies of up to 80%, but was unable to resolve infestations $<500\ m^2$ or mixed pixels with $<35\%$ leafy spurge. Similarly, AVIRIS, with a spatial resolution of 17 m for this activity, can map infestations of $\sim 160\ m^2$, and CASI (Compact Airborne Spectrographic Imager), with even higher 4-m spatial resolution can map infestations as small as $9\ m^2$ [16,17].

Indirect detection of species diversity through remote sensing of environmental parameters

The remote sensing of certain environmental parameters or indices can be used as an indirect method for discerning patterns of species diversity. Although it is probable that no single factor drives biodiversity patterns (e.g. the latitudinal gradient in species richness), investigators have long considered primary productivity, climate and habitat structure as important in determining species richness and distribution patterns [2–5]. Advances in remote sensing are providing relevant data about each of these three environmental parameters.

Technologies for the remote sensing of primary productivity for species richness

The nature of the relationship between primary productivity and species richness is still contentious. Exploring it at different spatial scales and in a variety of terrestrial and aquatic ecosystems, investigators have found positive linear, negative linear and unimodal or humped relationships as well as results showing no

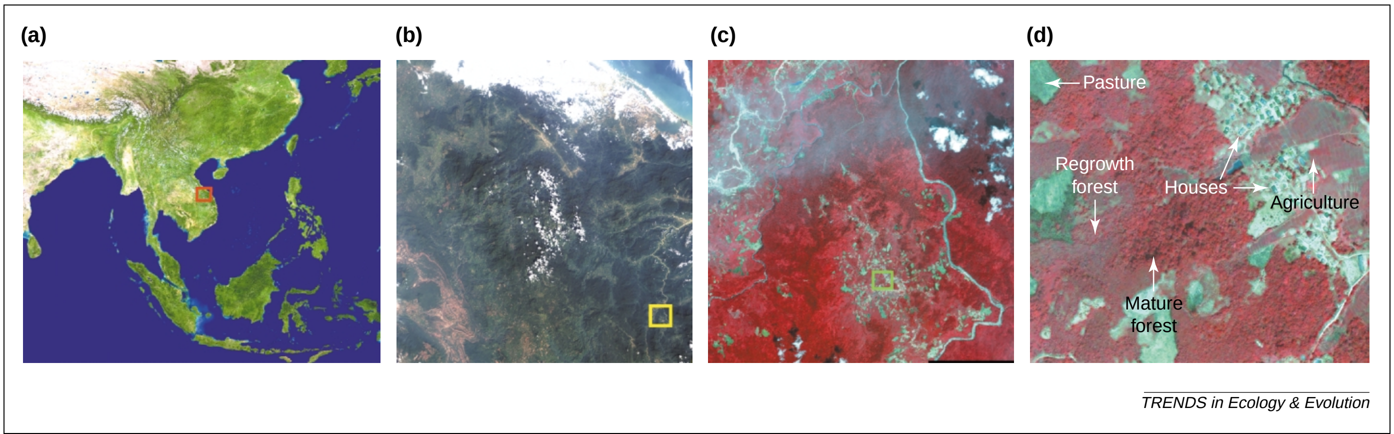

Fig. 1. Satellite images from three sensors at different spatial resolutions. (a) MODIS mosaic Southeast Asia. (b) Landsat 7 ETM + scene of central Vietnam. (c) IKONOS scene for $108.6\ km^2$ region near Song Thon Dac Pring; False color (= Color IR, Red, Green) and pan-sharpened. (d) IKONOS closeup showing different land-use types. Figure courtesy of AMNH/Ned Gardiner; IKONOS imagery from Space Imaging.

significant relationship [18]. Worm *et al.* [19] found a strong interactive effect between nutrient supply and consumer (food-web) pressures when looking at drivers of diversity in marine environments. Although there are many theories to explain the different productivity–diversity relationships, there is consensus about the need for more data linking patterns of primary productivity, large-area estimates of species richness and abundance, and more detailed information about the functional types of organism that occupy specific habitats and use resources in very different ways (S. Goetz, pers. commun.).

There are numerous remote sensing-based approaches for estimating primary productivity. Typically, multispectral satellite imagery available at spatial resolutions ranging from 4 m to 8 km provides a basis for primary productivity estimates at a variety of spatial scales. These estimates are often derived from one of several vegetation indices (e.g. the normalized difference vegetation index or NDVI) or direct measures, such as net primary productivity (NPP). The challenge for the researcher is to ensure that the scale of the imagery matches that of the species richness data and that both are scaled appropriately for the theory being tested [18,20]. For example, in watershed sediment yield models, the resolution and associated minimum-mapping unit of data derived from a given sensor greatly influenced the precision of results. Watershed sediment yield estimates varied over orders of magnitude when land cover, soil and topographic information were measured at different spatial resolutions from 30 m to 285 m [21].

Application of remotely sensed primary productivity to understanding species richness

In Oregon, USA, woody species richness is highest in areas of intermediate productivity, supporting a unimodal relationship. To show this, Waring *et al.* [22] used 1-km imagery from the Advanced Very High-Resolution Radiometer (AVHRR) instrument of the US National Oceanic and Atmospheric Administration (NOAA) to derive seasonal ratios of gross photosynthesis across Oregon. These ratios were then compared with plot data of woody plant species richness.

Technologies for the remote sensing of climate variables

The modeling of primary productivity via satellite data captures other environmental variables that might themselves be important to understanding spatial patterns of diversity. Many of these are climatic variables acting as probable limiting factors for many species (e.g. seasonal temperature, relative humidity and soil moisture). New sources of data and the implementation of a series of models that estimate some of these climatic parameters have become available since the launch of the US TERRA and AQUA satellites in 1999 and 2002, respectively. Moderate-Resolution Imaging Spectroradiometer (MODIS) sensors are aboard both satellites. MODIS has 36 spectral channels and produces imagery at spatial resolutions of 250 m, 500 m and 1 km. These relatively coarse resolutions and a broad viewing width mean regular global coverage from MODIS, (i.e. imagery of any location on Earth) every one to two days. Many of the satellite data products measured by or modeled from MODIS are new and require validation and re-calibration with field data (see Table 1). The availability of these and related products provides researchers worldwide with a common baseline for discussion and comparison. To make such information available, government agencies in the US and elsewhere are investing substantially in data management and distribution systems.

Application of remotely sensed climate variables to species distributions

Johnson *et al.* [23] used climate and NDVI data from the meteorological satellites of NOAA and the European Organization for the Exploitation of Meteorological Satellites (EUMETSAT) to predict areas of high bird species endemism in East Africa to an accuracy of 89%. Johnson *et al.* [23] also incorporated digital elevation data, which were the top-ranking predictor for most of their analyses. However, those cases in which elevation data were not used still showed predictive accuracies of 70–88%, with rainfall and thermal variables having the highest predictive power.

Technologies for the remote sensing of habitat structure and topography

Passive remote-sensing systems show us a two-dimensional world. Active systems bring the third dimension into play, making possible measures of habitat structure, biomass and topography. For example, in forests, lidar sensors use the return signals to detect the height of the canopy top, ground elevation, and the positions of leaves and branches in between. The Laser Vegetation Imaging Sensor (LVIS) is an aircraft-mounted lidar sensor, which has so far been flown over La Selva, Costa Rica, and various sites in the USA. NASA is investigating possibilities for developing a satellite-mounted lidar sensor, which would sample a large percentage of the surface of the Earth in a line-sampling mode. In 1994, the US Army Corps of Engineers developed the Scanning Hydrographic Operational Airborne Lidar Survey (SHOALS) system [24]. SHOALS, a marine lidar, collects accurate, high-resolution bathymetry data via helicopter.

The longer wavelength pulses of radars can penetrate clouds, and the longest radar wavelengths (i.e. L band and beyond) penetrate tree canopies – or, in cases of bare and loamy soil, the surface of the Earth to depths of a meter or more [25]. Although still a research application, the ability to penetrate forest canopies makes radar a potential tool for measuring biomass and determining vegetation structure.

For the first time, radar-derived datasets are also making available high-resolution topographic information for most of the land surface of the Earth. In 2000, NASA and the US National Imagery and Mapping Agency (NIMA) joined forces to launch the Shuttle Radar Topography Mission (SRTM) on the Space Shuttle Endeavour. Over the course of ten days, the SRTM radar system obtained elevation data from ~80% of the land surface of the Earth, virtually all land between +/−60° latitude. NASA and NIMA are now releasing SRTM digital elevation data to researchers. Horizontal postings (i.e. the distance between individual measures of elevation on the ground) being released are 30 m in the USA and 90 m elsewhere. Vertical resolutions (i.e. the ability of the sensor to correctly detect ground elevation differences) are of the order of 5 m [26]. Another source for remote sensing-derived elevation information is the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) sensor of Japan. ASTER detects reflected and emitted electromagnetic radiation at spatial resolutions of 15 m in the visible and near-infrared wavelengths, 30 m in the middle-infrared wavelengths, and 90 m in the thermal-infrared wavelengths. ASTER also produces digital elevation models (DEMs) of up to 10 m relative accuracy from stereo pair images, produced by imaging the same point on the surface of the Earth from different angles.

Applications of remote sensing for habitat structure and topography

Work by Nagendra [5] and Johnson *et al.* [23] reported improvements in classifying forest types and in predicting areas of bird endemism through the incorporation of elevation data. Data from LVIS enable the mapping of sub-canopy topography and canopy heights to within 1 m [27]. Going beyond elevation, recording numerous lidar return signals makes it possible to estimate vegetation density at different heights throughout the canopy and enables three-dimensional profiles of vegetation structure to be made. These data demonstrate the potential for applications such as mapping emergent tree species and sub-canopy layers that are important indicators of stratification for forest bird species (Fig. 2).

To date, the primary users of marine-based lidar have been port designers and beach engineers seeking to survey coastal dynamics (e.g. geomorphic changes and structural conditions), and to estimate sediment transport [28]. The application of lidar technology to marine biodiversity conservation shows considerable promise for detecting habitats in two major ways. First, when combined with optical remote sensing, lidar data enable scientists to calibrate reflectance so they can differentiate between water depth and changes in the sea floor. Second, models based on lidar-generated, fine-scale bathymetry data and biophysical parameters affecting the growth and population dynamics of many reef organisms (e.g. depth, exposure and suspended sediment concentration) should help us to predict the distribution of benthic communities as well as the processes governing the distribution of these communities (P. Mumby, pers. commun.).

Freshwater applications will also greatly benefit from new sources of data. Because interpretation of photographs does not provide a consistent method for mapping streams, automated stream channel identification methods that use elevation data have been developed over the past 25 years [29]. Higher resolution airborne radar or lidar sensors with X-, Y-, and Z-precisions of the order of 1 m hold tremendous potential for mapping stream channels, riparian systems, and floodplains. Terrain information is essential for models of surface processes (such as sediment yield), statistical analyses of the spread of invasive species, and detecting habitat conditions [21,30]. Elevation data underlie powerful visualizations of

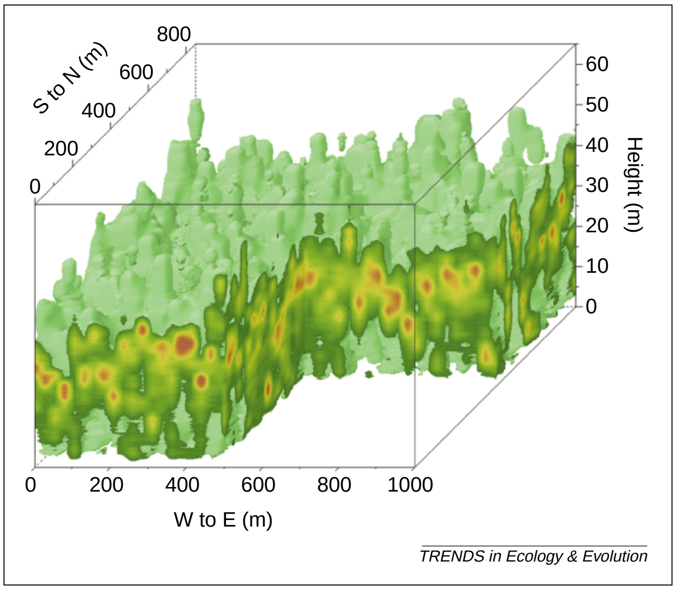

Fig. 2. Volumetric rendering of intercepted rain forest canopy surfaces from La Selva, Costa Rica taken with Laser Vegetation Imaging Sensor in March 1998. Figure courtesy of John Weishampel, University of Central Florida.

well known phenomena. Researchers often use such data to understand the distribution of different land uses across landscapes, and the interaction of land use and topography has important effects on water quality [31]. When Landsat 7 imagery is draped over SRTM elevation data, watershed land use can be compared to expectations, and resultant water-quality conditions, species assemblages and habitat conditions can be predicted [32].

Caveats

There are major challenges involved in working with remote-sensing data. First, costs for imagery and other data products are often high. In general, imagery from the newer and higher spatial resolution hyperspatial satellites is more expensive than lower resolution imagery. Although the overall trend is toward declining imagery costs (Box 3), handling even small quantities of satellite imagery requires special software and hardware tools. Increases in computational power are driving down the costs of necessary computer hardware while the costs of remote sensing and geographical information system (GIS) software are also declining. Nevertheless, these costs are not negligible. An even greater challenge for ecologists and conservation biologists hoping to incorporate remote-sensing technologies into their work is the technical expertise required to handle imagery and other data products. Training and hours spent working with the imagery are a prerequisite for understanding what one is looking at. Fortunately, new software tools are making remote-sensing data more accessible. That said, many of the remote-sensing data types discussed here (hyperspectral, lidar and radar) are still largely or exclusively in the research phase of development and might currently be beyond the capabilities of most researchers. Another point to emphasize is the tremendous importance of getting accurate information to validate what the remote-sensing data products appear to be telling the user. Such 'ground-truth' information might come from researchers in the field, ground-based sensors, or even higher resolution remote-sensing sources (e.g. aerial photography). Remote-sensing products should not be taken at face value. Atmospheric phenomena, mechanical problems with the sensor and numerous other effects might be distorting one's view. Finally, although they are not discussed here, ecological models have a vital role in the process of converting remote-sensing data products into actual knowledge of species distributions and richness. Applying these models also requires additional software and analytical skills.

Prospects

Understanding the environmental drivers of species distributions and levels of species richness and how they operate in different geospatial contexts is a fundamental challenge of modern biology. This challenge is made all the more urgent by the ongoing and escalating loss of biodiversity. If we are to stem this loss, we must know where the species are that we are trying to conserve and what areas of the Earth are especially rich in species. But to be truly successful, we must also understand, at a deeper level, why species are located where they are and why certain areas are species rich or characterized by high levels of endemism. The launch of many new satellite systems over the past five years and the development of new technologies, some available only on airborne platforms, have given us an unprecedented number of remote-sensing tools with which to address these challenges. These tools are found in both the public and private sectors of the economy and are not limited to any particular country or region.

The largest obstacle to applying these tools to both the scientific and conservation challenges before us are, for the first time, probably more cultural than technological. A perception problem continues to exist, even among those directly involved in developing and promoting remote-sensing systems: the belief that the spatial scales provided by remote-sensing systems and those addressed by ecologists, evolutionary biologists and conservation biologists still do not match. This perception has probably prevented many otherwise interested and concerned remote-sensing researchers from pursuing the problems of greatest relevance to their colleagues in the biological sciences, and has kept most biologists from considering remote sensing as a useful tool. We believe it continues to do so today. New tools are slowly overtaking this false perception. The direct remote sensing of certain aspects of biodiversity is now possible. But as important, if not more, indirect approaches to the remote sensing of biodiversity hold the promise of not only getting better estimates of species distributions and richness levels, but of also shedding light on the processes underlying them.

To make progress, ecologists, evolutionary biologists and conservation biologists must bring their data sets on species distributions, levels of species richness, areas of endemism, and so on, to the table and combine them with the global, regional and local data sets of, for example, primary productivity and climate, which have been generated by remote-sensing researchers. This is already starting to occur in remote-sensing laboratories around the world. Simultaneously, many newly emerging ecologists, evolutionary biologists and conservation biologists are beginning to include remote sensing and GIS experience in their professional toolkits. This is also a welcome development. However, time is our enemy in this regard. Biodiversity loss will not wait for the development of new graduates and undergraduates to the point where they can influence environmental policy. What is needed is more collaboration now among remote-sensing researchers and those working in biodiversity science and conservation. The tools are there. Let us hope that the users will soon follow.

Acknowledgements

The workshop 'Biological Fingerprinting: Using Remote Sensing for the Improved Modeling and Monitoring of Biodiversity' was both an inspiration and a source for much of the information in this review. The American Museum of Natural History hosted the workshop from 3–5 December 2001, co-sponsored with the Center for Applied Biodiversity Science at Conservation International, NASA and Columbia University. Stuart Pimm, Gustavo Fonseca, Peter Mumby, Keya Chatterjee, Scott Goetz, Ralph Root, Ned Horning and Steve Running provided ideas, comments and reviews for this article. We thank Richard Waring, Ralph Root, and Tom Brooks for access to material in press or review and Jennifer Stenzel for help with editing.

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