From space to species: ecological applications for remote sensing

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A variety of ecological applications require data from broad spatial extents that cannot be collected using field-based methods. Remote sensing data and techniques address these needs, which include identifying and detailing the biophysical characteristics of species' habitats, predicting the distribution of species and spatial variability in species richness, and detecting natural and human-caused change at scales ranging from individual landscapes to the entire world. Such measurements are subject to substantial errors that can be difficult to overcome, but corrected data are readily available and can be of sufficiently high resolution to be integrated into traditional field-based studies. Ecologists and conservation biologists are finding new ways to approach their research with the powerful suite of tools and data from remote sensing.

Human activities now affect most of the terrestrial biosphere and are increasing in intensity and extent. Ensuing habitat loss and degradation impair ecosystem function [1] and reduce the value of ecosystem services for humans [2]. Although ecologists are improving their understanding of the factors limiting the distribution of species [3], extinction rates continue to accelerate [4,5]. The need to be able to detect and predict changes in the natural environment has never been greater. However, traditional field ecological data do not translate readily to regional or global extents, and models derived purely from such local data are unlikely to predict the global consequences of human activities. Therefore, ecologists and conservation biologists are turning to the rapidly developing discipline of remote sensing to provide the techniques and data sources necessary to prepare scientific responses to environmental change. Although the need for remote sensing is especially urgent for conservation-related science, satellite-based earth observations are also being used for basic ecological research.

Satellite remote sensing data are subject to large errors that, if uncorrected, substantially reduce their utility for ecological applications. Before reflected radiation reaches a satellite, it interacts with two 'noisy' environments: the surface of the Earth and the atmosphere. Atmospheric contamination of the remote sensing signal can arise through interaction with ozone, water vapour, aerosols, and other atmospheric constituents (e.g. [6]). On a cloudy day, satellite-borne optical remote sensors (Box 1) see little but the tops of clouds. Shadows, particularly when they vary across the fields of view of sensors that see across broad areas [e.g. Advanced Very High Resolution Radiometer (AVHRR) or Vegetation (VGT) sensors], haze and scatter from terrestrial surfaces can severely reduce data consistency and such effects are very difficult to remove [7]. Although long-wave, active remote sensing systems (e.g. synthetic aperture radar) are much less affected by the vagaries of the weather, they are subject to their own suite of shortcomings, and optical remote sensing data are still used more widely for ecological applications. Fortunately, many freely available remote sensing data sets (Table 1) have already been processed to reduce contamination and other errors and are readily available for ecological research.

Here, we discuss recent ecological and conservation applications of satellite remote sensing data as well as some of the limitations inherent to measurements frequently taken from >700 km above the surface of the Earth. Remote sensing generates a remarkable array of ecologically valuable measurements, which includes the details of habitats (land cover classification) and their biophysical properties (integrated ecosystem measurements) as well as the capacity to detect natural and human-induced changes within and across landscapes (change detection). Although there is a perceived mismatch between broad-scale remote sensing and local-scale field ecological data (Box 2), remote sensing is providing the impetus for an increasingly wide range of ecological and conservation biological discoveries.

Land cover classification

Satellite remote sensing can be used to estimate the variety, type and extent of land cover throughout a study region, meeting a fundamental need that is common to many ecological applications. Land cover data describe the physiographical characteristics of the surface environment, which can range from bare rock to tropical forest [8] and that are usually derived by applying statistical clustering methods to multispectral remote sensing data (Fig. 1). Remote sensing can also assist in the development of land use data that reflect human interactions with the physical environment, although the relationship between land cover and land use [9,10] is not necessarily one-to-one (e.g. forest and grassland are different land covers but they can have the same recreational land use if they are both found within a park). Depending on the remote sensing and field-based resources available, land cover

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Box 1. From pixels to properties of ecosystems

Ecological applications of remote sensing draw most extensively on a few satellite-borne optical remote sensors that vary in their respective spatial and temporal resolutions (Table I). Spatial resolution refers to the pixel size of the data collected by the sensor. For example, Landsat collects relatively high resolution imagery (clearly focused, with pixels ranging from 15 m to 60 m across), whereas Advanced Very High Resolution Radiometer (AVHRR) collects coarse resolution imagery (pixels are >1 km across). Temporal resolution refers to the frequency with which sensors can collect data from the same place. AVHRR and Vegetation (VGT) sensors collect data from a particular region every day, whereas Landsat 7 returns every 16 days. The multispectral data collected from such sensors can be combined or used as input for models to develop measurements of the biophysical properties of ecosystems. Normalized Difference Vegetation Index (NDVI) combines reflected red and near infrared (NIR) radiation according to the simple equation: $NDVI = (NIR - RED)/(NIR + RED)$. Through its strong correlation with aboveground net primary productivity and absorbed photosynthetically active radiation, NDVI provides an index of ecosystem function. There are, however, many alternative vegetation indices that serve more specific purposes or that can reduce some errors associated with NDVI, such as sensitivity to differences in soil reflectance or nonlinear relationships with ecological properties, such as leaf area index [7,45,46]. Remote-sensing estimates of land surface temperature require relatively complex calculation and ancillary data but can be used to measure accurately and precisely surface temperature [47].

Table I. Characteristics and applications of commonly used multispectral satellite sensors

Sensor	Spatial resolution (m)	Band[a]	Spectral range (μm)	Common applications
Landsat 7 ETM + [b]	15–120	Blue	450 to 0.515	Coastal water mapping; differentiation of vegetation from soils
		Green	0.525 to 0.605	Assessment of vegetation vigor
		Red	0.63 to 0.69	Chlorophyll absorption for vegetation differentiation
		NIR	0.75 to 0.90	Biomass surveys and delineation of water bodies
		MIR	1.55 to 1.75	Vegetation and soil moisture measurements; differentiation between snow and cloud
		TIR	10.4 to 12.50	Thermal mapping, soil moisture studies, plant heat stress measurement
		MIR	2.09 to 2.35	Hydrothermal mapping
		PAN	0.52 to 0.90	Large area mapping, urban change studies
NOAA-16[c] AVHRR	1100–4000[d]	Red	0.58 to 0.68	Global vegetation monitoring, forest fire activity, canopy gaps
		NIR	0.725 to 1.00	Global vegetation monitoring, forest fire activity, canopy gaps
		MIR	3.55 to 3.93	Land-water boundaries, global vegetation monitoring, forest fire activity, canopy gaps
		TIR	10.30 to 11.30	Sea surface temperature, volcanoes, and forest fire activity
		TIR	11.50 to 12.50	Sea surface temperature, urban studies (urban heat island effect)
SPOT 4, SPOT 5[e] (Vegetation)	1000	Blue	0.43 to 0.47	Detection of very low vegetation cover (minimized atmospheric reflectance)
		Red	0.61 to 0.68	Plant canopy characterization, forest and agricultural monitoring
		NIR	0.78 to 0.89	Canopy structural properties
		MIR	1.58 to 1.75	Canopy structure and water content of leaves

[a]Abbreviations: MIR, middle infrared; NIR, near infrared; PAN, panchromatic; TIR, thermal infrared. Bands are listed according to sensor-specific numbering schemes (e.g. Landsat 7 Band 1 detect blue radiation).
[b]Landsat 5 Thematic Mapper and Landsat 7 Enhanced Thematic Mapper + have variable spatial resolutions. Nonthermal bands 1–7 have pixel resolutions of 30 m. Landsat 5's thermal channel has a 120 m resolution, whereas the thermal channel of Landsat 7 has a resolution of 60 m. Landsat 7 has an additional, panchromatic channel, which has a resolution of 15 m.
[c]NOAA-14 has channel 3 (3.55–3.93 μm) only. NOAA-16 alternates between daytime reception of NIR and nighttime reception of MIR.
[d]AVHRR has a pixel resolution of 1100 m at nadir and 4000 m at the edges of its field of view.
[e]These satellites also carry two HRVIR instruments, the High Resolution Visible and Infrared, that collect localized data in the same spectral bands as the Vegetation instrument but at resolutions of 10–20 m (the modified HRVIR system on SPOT5 includes a panchromatic channel with a maximum 2.5 m resolution).

classifications can identify very specific habitats. The National Vegetation Classification System (NVCS; http://biology.usgs.gov/fgdc.veg/) is a standard land cover classification system that was developed cooperatively by several major scientific and conservation organizations, including The Nature Conservancy and Ecological Society of America, and which continues to evolve. It is now widely used for wildlife habitat modeling. Different land cover classification approaches vary in their potential for discerning detail (Fig. 1) and, consequently, their utility for meeting specific needs (e.g. the identification of all examples of a particular habitat) [11]. Regardless of the approach taken, validation of the classification results is needed to estimate and, where necessary, improve land cover classification accuracy. Ground-truth data are most commonly used for this purpose and comprise positive identification of examples of each land cover of interest that are then used to test classification accuracy.

Land cover data have proven especially valuable for predicting the distribution of both individual species [12,13] and species assemblages [14] across broad areas that could not otherwise be surveyed. Various predictive models have gained currency as the availability and accuracy of land cover data sets have improved. The Gap Analysis Program (GAP) is the largest species distribution modeling effort and aims to develop detailed maps of habitat preferences for target species. The primary products from GAP are readily available (Table 1). Climatological, biophysical and land cover data can also be integrated to predict the presence and absence of individual species throughout their ranges with the use of genetic algorithms (http://biodi.sdsc.edu/) or logistic

Table 1. Online remote sensing data sources, sensor descriptions, and learning resources[a]

Data source/Information link	Spatial resolution (m)	Description	URL
Freely available satellite data sets for ecological applications			
Global and NDVI	1100–4000	AVHRR global/continental land cover products using six different classification schemes. Monthly NDVI composites. Data derived from 1992/1993	http://edcdaac.usgs.gov/glcc/glcc_version1.html#Global
SPOT/VGT composites	1000	10-day composites available from 1998 to present for SPOT4/SPOT5 VEGETATION sensors	http://free.vgt.vito.be/
University of Maryland Global Land cover Facility	Various	Very large satellite data archive including land cover products and processed satellite imagery with global coverage	http://glcf.umiacs.umd.edu/index.shtml
Global Land Cover 2000	1000	Global land cover mapping initiative based on VEGETATION data; will comprise a core data set for the global Millennium Ecosystem Assessment	http://www.gvm.sai.jrc.it/glc2000/defaultGLC2000.htm http://www.millenniumassessment.org
CORINE data page	250	High-resolution European land cover data	http://dataservice.eea.eu.int/dataservice/metadetails.asp?table=landcover&i=1
Canadian spatial data	Various	Various satellite and geospatial data	http://geogratis.cgdi.gc.ca/frames.html
USGS Gap Analysis Program	30	Classified Landsat 7 land cover data (based on NVCS) and species' habitat suitability maps	http://www.gap.uidaho.edu/
Global Fire Monitoring Centre	Various	Near-real time fire detection and mapping	http://www.fire.uni-freiburg.de/current/globalfire.htm
Global Burnt Area 2000	1000	Global mapping of burnt areas throughout 2000 from VEGETATION data	http://www.gvm.sai.jrc.it/fire/gba2000_website/index.htm
Home pages for commonly used sensors			
AVHRR	1100	Description of AVHRR data and various NOAA satellite missions	http://edcdaac.usgs.gov/1KM/avhrr_sensor.html
SPOT4/SPOT5	1000	Description of SPOT4 and SPOT5 missions and sensors (including VGT1 and VGT2 sensors, as well as HRVIR)	http://www.spotimage.fr/home/
Landsat 7	15–60	Description of sensor and data characteristics	http://landsat.gsfc.nasa.gov/
MODIS	250–1000	Description of sensor and data characteristics	http://modis.gsfc.nasa.gov/
Remote-sensing learning resources			
		Online remote sensing tutorials	http://www.ccrs.nrcan.gc.ca/ccrs/learn/learn_e.html http://rst.gsfc.nasa.gov/start.html http://www.research.umbc.edu/~tbenja1/

[a]Abbreviations: AVHRR, Advanced Very High Resolution Radiometer; CORINE, Coordination of Information on the Environment; HRVIR, High Resolution Visible and Infrared; MODIS, Moderate Resolution Imaging Spectroradiometer; NDVI, Normalized Difference Vegetation Index; NOAA, National Oceanic and Atmospheric Administration; NVCS, National Vegetation Classification System; SPOT, Système Probatoire d'Observation de la Terre; USGS, US Geological Survey; VGT, Vegetation sensor onboard SPOT 4 and 5 satellites.

models [15]. At broader scales, habitat heterogeneity data derived from thematically detailed land cover predicts Canadian butterfly species richness and community similarity better than does any other factor yet discovered [14].

Successful prediction of species distributions with the use of land cover data depends on the characteristics of the species. For species that do not occupy all suitable habitats for any reason (such as for species with metapopulation structure), land cover maps might predict only potential rather than actual species distributions. For example, the presence of particular butterfly, plant, or bird species in Yellowstone National Park is predictable when they have specific habitat requirements, they are abundant, or both. The actual distributions of rare species that are not specific to particular habitats could not be predicted from even remarkably detailed and accurate land cover data [13]. Land cover classifications used for wildlife habitat modeling must be of sufficient spatial and thematic resolution to identify reliably the habitats that the target species potentially occupy (Box 2). It will almost certainly be necessary to collect *in situ* (or other ancillary) measurements to meet such stringent requirements for predicting the realized distributions of many species.

Integrated ecosystem measurements

Unlike field-based measurements of ecosystem function, which cannot easily be converted to estimates of function across entire ecosystems, remote sensing can provide simultaneous estimates of ecosystem function over wide areas. Remote sensing of vegetation offers promising and urgently needed measurements of ecosystem function at spatial scales that are most comparable to the extents of human-caused environmental change (Box 2). Net primary productivity (NPP) represents one aspect of integrated ecosystem function for which the normalized difference vegetation index (NDVI, Box 1) is used, particularly

Box 2. Combining remote sensing and ecological measurements

Solutions to the problem of scale mismatch between traditional field ecological data and most remote sensing data sources will probably be application-specific [48]. As with many scale issues in ecology, this problem is simple, at least conceptually: studies in the field provide detailed measurements over small areas at different times, whereas the most commonly used remote sensing data provide synchronous measurement of broad areas but with reduced potential for local detail (Fig. I). Ecological and remote sensing data can be linked by defining a nested set of sites to be sampled with the use of field techniques, which fall within larger areas containing habitats that are identifiable by remote sensing [49]. Although such a detailed approach will not always be necessary, interpretations from remotely sensed data sets will frequently be suspect if they are not supported by reliable field data. Even relatively high resolution (e.g. at 20 m) remote sensing data might be insufficient to identify landscape and habitat factors needed to predict the occurrences of some species [13]. This perceived 'scale gap' is narrowing, however, with the increasing availability of very high-resolution data that can be linked directly to traditional field ecological measurements [50].

The key habitats of species can be identified by combining satellite- and field-based habitat data, landscape structure and species abundance information [13,51]. Measurements of genetic diversity can also be related to landscape attributes to make spatially explicit predictions of species occurrence [51]. With such data in hand, both species and genetic diversity can be monitored over time. Detailed satellite land cover data can identify habitat boundaries and biophysical characteristics, such as productivity, that could not be discerned from hand-drawn maps (e.g. topographical maps) that include little detail within habitat types or ecotones. Habitat edges, such as riparian buffer zones, are important as species refugia and for their ecosystem functions of modulating sediment and nutrient flux. Factors known to affect pathogen and pest abundance, such as host availability, habitat quality and climatic conditions, can also be modeled and predicted with the use of remote sensing data [52,53] as well as the distribution of particular vectors, especially when combined with field-based collections [54].

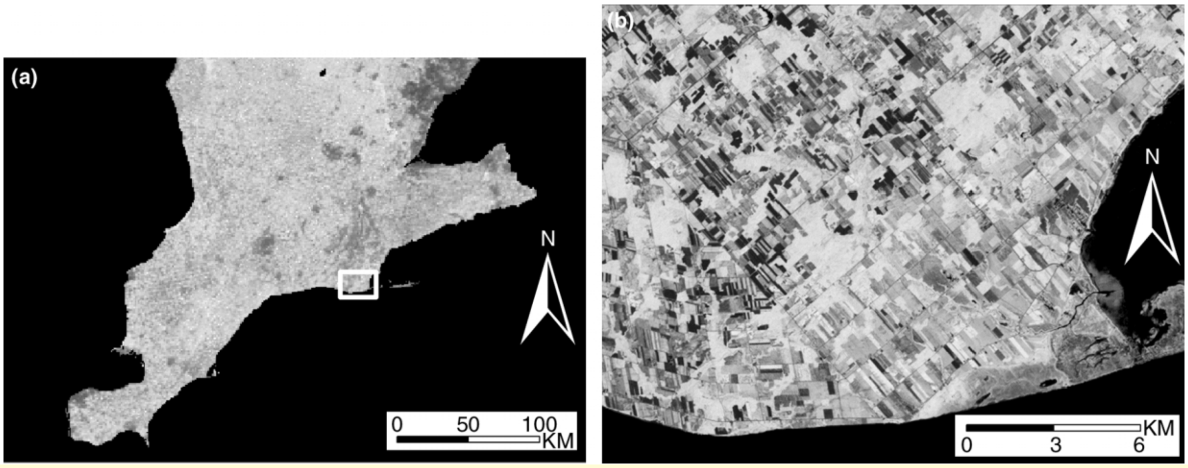

Fig. I. Ecosystem function indexed by low and high-resolution imagery. NDVI (Normalized Difference Vegetation Index) varies continuously with the amount and vigor of vegetative cover. (a) Coarse resolution NDVI measurements (SPOT4/Vegetation composite from July–August 1998 over southern Ontario, Canada, 1 km pixels) show strong contrasts between urban (low NDVI, darker masses) and vegetated areas (high NDVI, brighter areas). (b) comprises relatively high-resolution NDVI data from the boxed area in (a) (Landsat 7 ETM + path 18, row 30, September 3, 2000, 30 m pixels). Highly productive forest remnants, essential for wildlife conservation in Canada, are shaded most brightly.

when refined with meteorological and soil data [16]. NDVI also correlates strongly with absorbed photosynthetically active radiation (APAR), which has helped lead to its common use as an estimator of aboveground NPP [17,18]. Similar to NPP, NDVI is sensitive to changes in both temperature and precipitation [16,19].

NDVI measurements, especially when combined with land use data, are increasingly important to studies that must differentiate between natural variation in ecosystem function and variation arising from human activities, such as habitat conversion. In a study of native grasslands and cultivated fields, land use emerged as the most important influence on ecosystem function as measured by integrated annual NDVI [20]. NDVI is also considerably more variable in highly agricultural and urban areas [21] and is strongly related to the extent of vegetation cover [22] (Box 2). It can be used to detect land cover changes (e.g. forest replacement by agriculture [23]) and as an indicator of both landscape heterogeneity and biological diversity, making it possible to identify priority conservation areas [24] and predict habitat suitability for species [25]. NDVI is no panacea, however: as with most remote sensing data, it is error-prone in regions of high topographical relief [26]. It also does not relate simply to some ecological parameters that interest many biologists, such as leaf area index (LAI) [27] and can be influenced by the reflectivity of substrates underlying partial vegetation covers. A host of other vegetation indices are available that might be better adapted for some applications or that correct for some of the errors to which NDVI is subject (e.g. reduced simple ratio vegetation index more directly estimates LAI [7]). NDVI, however, remains the most commonly used and most intensively studied vegetation index.

Other integrated measures of ecosystem function, such as surface brightness temperature (T_s), are used by the remote sensing community but relatively rarely by ecologists (Box 1). T_s measures the amount of emitted thermal energy and the energy efficiency of terrestrial ecosystems [28]. Modifications to ecosystem energy budgets follow many human or natural disturbances, particularly if these lead to simplification of ecosystem structural properties,

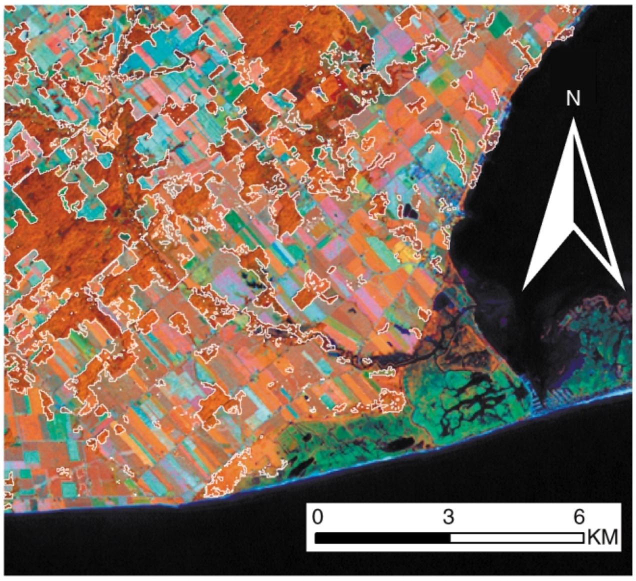

Fig. 1. Identifying habitats through land cover classification. A multispectral image from southern Ontario, Canada just south of Toronto based on Landsat 7 imagery (path 18, row 30, September 3, 2000, 30 m pixels) that indicates the potential for land cover detail at this resolution. It is derived from the near infrared, middle infrared, and red channels (i.e. band combination 4,5,3) from the remote sensing imagery. Outlined areas are major forest habitat remnants that are home to many endangered species.

and characteristic changes to T_s can follow [29]. Brightness temperature is less widely used than is NDVI as an index of ecosystem function but has significant potential for this purpose.

Change detection

Ecological studies increasingly require biophysical and habitat data through time and over significant areas, a task for which remote sensing is especially powerful. Near-global-scale remote sensing data sets have been available continuously since the early 1980s from a series of meteorological satellites carrying AVHRR (Box 1). Most AVHRR data are readily accessible (Table 1) and provide the only near-continuous, long-term (~21 years) measurements of key ecological parameters, such as habitat extent, heterogeneity or primary productivity, at regional or global scales. Landsat sensors have been collecting data for even longer (since the early 1970s) and have better spatial resolution than do AVHRR or Vegetation (15–120-m pixels versus ~1-km pixels; Box 1). Landsat data cannot provide near-real time ecosystem monitoring across broad areas because of the relatively long site revisit times of the satellite (16–18 days). However, the Landsat data record is the longest of any satellite and its improved spatial resolution enables the detection of subtle environmental changes that could be missed by coarser resolution sensors.

Climate change

Remote sensing data have provided convincing evidence that climate has been changing rapidly [30], complementing ecological discoveries of poleward shifts in the ranges of many species [31,32]. Although the distributions of species have also responded to concurrent land use changes [33], time series AVHRR data demonstrate that substantial alteration to vegetation structure, primary productivity and growing season length have occurred even over the past 20 years. In boreal forests, which studies increasingly indicate to be crucial sinks for carbon dioxide, long-term analysis (1981–1999) of NDVI trends show a general increase in growing season length, annual primary productivity and northward extension of the treeline [34,35]. Integrated NDVI (the sum of NDVI measurements from all AVHRR composites measured throughout the growing season) correlates with field-based measurements of net primary productivity, biomass accumulation and temperature. Warming, moistening trends have also been detected with the use of AVHRR and more specialized sensors over marine systems [36], providing important corroborative evidence of climate change. Widespread, synchronous coral bleaching events are due primarily to increasing sea temperatures and can be monitored with the use of Landsat 7 ETM + data [37]. Several biological consequences of climate change can be observed remotely, but field-based research also provides convincing corroboration of biotic consequences of climate change [38,39].

Habitat loss

Satellite measurements of broad-scale trends in vegetation provide direct estimates of habitat loss, increasing the power of applied ecological studies to detect changes in species distributions or model extinction rates. Deforestation in humid tropical forests, which house many terrestrial biodiversity hotspots, is a globally leading cause of species loss [40,41]. It has proven very difficult to estimate accurately the extent of humid tropical deforestation because of poor monitoring infrastructure in many countries and inconsistencies among existing monitoring regimes. Satellite data from the 1990s, based on AVHRR and SPOT4/Vegetation and supplemented by high-resolution Landsat and SPOT4/HRVIR (high resolution visible and infrared) data, have been integrated to generate the best estimates yet of rates of deforestation among remaining humid tropical forests [42]. These new data demonstrated that these rates were ~23% lower than FAO (Food and Agriculture Organization) estimates. Deforestation 'hotspots' could also be detected. Fire, another leading source of change, can be especially extensive in areas that have previously been damaged by deforestation. A combination of AVHRR, Landsat TM (Thematic Mapper) and radar data were used to detect the impact of deforestation on the burn likelihood of forests in East Kalimantan, Indonesia [43]. Forests that were undisturbed or had been logged long ago were far less likely to be included in the massive fire event of 1997/1998 and were also subject to less intense fire damage. In total, 5.7% of unlogged forests were affected by the fire, compared with 59% of forests that were subject to recent logging disturbances. These forest fires, which burned part of the underlying peat substrate, also emitted a massive pulse of carbon dioxide that comprised between 13% and 40% of the total global annual carbon dioxide release from fossil fuel burning [44]. Satellite detection of fires now occurs in near-real time throughout much of the world (based especially on AVHRR and MODIS, the Moderate Resolution Imaging Spectroradiometer) and global burned area mapping initiatives, such as Global Burnt Area 2000 (Table 1), are in progress.

Conclusion

Remote sensing is indispensable for ecological and conservation biological applications and will play an increasingly important role in the future. For many purposes, it provides the only means of measuring the characteristics of habitats across broad areas and detecting environmental changes that occur as a result of human or natural processes. These data are increasingly easy to find and use. Although field and remote sensing data are often collected at divergent spatial scales, ecologists have begun to recognize both the potential and the pitfalls of satellite information. Established remote sensing systems provide opportunities to develop and apply new measurements of ecosystem function across landscapes, regions and continents. New efforts to predict the consequences of ecosystem function change, both natural and human-induced, on the regional and global distributions and abundances of species should be a high research priority. The full range of remote sensing techniques for identifying land covers, measuring the biophysical properties of ecosystems and detecting environmental change will need to be integrated with existing and new ecological data to meet this ambitious challenge.

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