Terrestrial Vegetation in the Coupled Human-Earth System: Contributions of Remote Sensing

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Annu. Rev. Environ. Resour. 2008. 33:369–90

First published online as a Review in Advance on August 1, 2008

The *Annual Review of Environment and Resources* is online at environ.annualreviews.org

This article's doi:
10.1146/annurev.environ.33.020107.113339

1543-5938/08/1121-0369$20.00

Key Words

biogeochemical cycling, ecosystem management, ecosystem services, land cover, satellite data

Abstract

The Earth system and society's use of ecological resources are tightly coupled through exchanges of water, energy, and nutrients. Terrestrial vegetation transfers materials between the atmosphere, biosphere, and water bodies in the coupled system. Vegetation is also a primary interface between human society and the Earth system through land-cover conversion, cultivation of favorable species, and transfer of organisms between locations. Remote sensing aids analyses of these interactions and, ultimately, contributes information to decision makers for improved management. Multidecadal records from multispectral sensors have been the mainstay for studying terrestrial vegetation at regional and global scales. Representation of vegetation and carbon dynamics is now routine in Earth system models. Challenges remain to incorporate realistic ecological disturbances and human land-use activities based on remote sensing observations. Hyperspectral, LIDAR, and radar systems contribute new capabilities for observing nitrogen fluxes, vegetation stress, canopy structure, and in some cases individual species.

Contents

INTRODUCTION

The coupled system that exchanges water, energy, and nutrients among the land, atmosphere, and oceans at multiple temporal and spatial scales is the basis for human civilization and all other life on Earth. Terrestrial vegetation performs many pivotal roles in the coupled Earth system. Photosynthesis converts the sun's energy into forms usable by humans and other animals. Vegetation stores carbon that would otherwise reside in the atmosphere as a greenhouse gas, thereby regulating climate. Organisms obtain nitrogen through plants as one step in transforming unusable atmospheric nitrogen to usable forms essential for growth. Finally, terrestrial vegetation transfers water between belowground reservoirs and the atmosphere to maintain precipitation and surface water flows.

Spectral resolution: the ability of the sensor to differentiate wavelengths in the electromagnetic spectrum

AVHRR: Advanced Very High Resolution Radiometer

In addition to these ecological functions, terrestrial vegetation is one of the main interfaces between human societies and the Earth system. Human societies have transformed large portions of Earth's vegetation to grow a small number of suitable plant species for food and fiber. Today, approximately 24% of Earth's land surface is cultivated to support increasing numbers of people consuming increasing quantities of these species (1). Livestock graze on nearly all available grasslands, and managed grazing occupies about 25% of the land surface (2, 3). The accelerating pace of these transformations in the past 50 years is the basis for concerns about negative consequences for biodiversity, climate regulation, and other ecosystem services (4).

Scientists have recognized these myriad roles and the consequences of human transformation of Earth's vegetation as far back as Plato (5). But the ability to view Earth's vegetation from space fundamentally altered opportunities to study the ecological role and human transformation of Earth's vegetation over broad scales and through time (**Table 1**).

Early satellites for Earth observations, such as the Television Infrared Observation Satellite (TIROS-1) launched in 1960, were not intended to study vegetation. Rather, they focused on weather analysis and forecasting (6). By the next decade, however, scientists were applying these observations to vegetation studies (7, 8). Although the spatial and spectral resolutions of Advanced Very High Resolution Radiometer (AVHRR) sensor onboard TIROS were not ideal for vegetation analyses, these studies exploited the properties of chlorophyll *a* pigment to absorb wavelengths in the red spectral region and structural properties of leaves to reflect near-infrared spectra. The synoptic, daily view of the coupled atmosphere-biosphere as photosynthesis sequestered carbon from the atmosphere in the Northern Hemisphere summer (9) opened possibilities for global perspectives in ecology.

Table 1 Types of sensors and their utility for remote sensing of terrestrial vegetation[a, b]

Sensor characteristics	Passive				Active	
	Coarse-resolution multispectral	High-resolution multispectral	Hyperspatial	Hyperspectral	LIDAR	Radar
Spatial resolution	Low (250 m–8 km)	High (10–50 m)	Very high (<5 m)	Very high (4–20 m)	Very high	High
Spatial coverage	Global	Limited before 1990; global since 1990 (as individual scenes of varying size)	Very limited	Very limited	Very limited	Global
Temporal resolution[c]	Daily since early 1980s	16 days since 1970s	No regular repeat cycle	No regular repeat cycle	No regular repeat cycle	Several times/year
Spectral resolution	Low (<10 bands, visible – TIR)	Low (<10 bands, visible – TIR)	Low (<5 bands visible-NIR)	High (>200 bands in visible-IR)	–	–
Example sensors	AVHRR, MODIS, SPOT Vegetation	Landsat ETM+, SPOT HRV, CBERS, ASTER, LISS	QuikBird, Ikonos	AVIRIS, Hyperion	LVIS	PALSAR, ASAR, GLAS
Examples of utility to Earth system science	Global/continental vegetation mapping; long-term vegetation productivity; active fire and burn scars	Land-cover change; habitat mapping; urban growth	Validation and calibration of coarser resolution; mapping tree crowns; urban patterns	Leaf water and nitrogen content, invasive species; building materials	Canopy structure; habitats	Canopy structure; biomass

[a]Characteristics of the sensors reflect current capabilities and will change as new sensors are launched in the future.
[b]Abbreviations: ASAR, Advanced Synthetic Aperture Radar; ASTER, Advanced Spaceborne Thermal Emission and Reflection Radiometer; AVHRR, Advanced Very High Resolution Radiometer; AVIRIS, Airborne Visible/Infrared Imaging Spectrometer; CBERS, China-Brazil Earth Resources Satellite; ETM, Enhanced Thematic Mapper; GLAS, Geoscience Laser Altimeter System; LISS, Linear Imaging Self-Scanning; LVIS, Laser Vegetation Imaging Sensor; MODIS, Moderate Resolution Imaging Spectroradiometer; NIR, near infrared; PALSAR, Phased Array-type L-band Synthetic Aperture Radar; SPOT HRV, Le Système Pour l'Observation de la Terre High Resolution Visible; TIR, thermal infrared.
[c]Temporal resolution: the frequency of coverage of a sensor.

The Landsat program, specifically designed to map land resources with finer spatial resolution than the AVHRR, also provided observations for a wide range of studies on terrestrial vegetation. The program was the first civil, nonweather satellite program and launched its first satellite in 1972. Landsat provided the capability to observe any place on Earth once every 18 days. The initial purpose was timely identification of crop yields, first wheat in the midwestern United States and then wheat, corn, and rice in other countries (10, 11). Seven Landsat sensors have since been launched with additional spectral bands and improved spatial resolution. These data have been the backbone for land-cover studies. Several countries currently have similar sensors in orbit (**Table 1**), although complete global coverage on an annual basis is still not available.

Concern about anthropogenic impacts on the Earth system underlay the scientific rationale for NASA's Earth Observing System (EOS) launched in 1999 (12). The program brought new capabilities for monitoring

Electromagnetic spectrum: ranges from shorter (gamma and X rays) to longer (microwaves) wavelengths. Different materials radiate and emit energy in different wavelengths terrestrial productivity and other vegetation properties through near-daily, global coverage. The multispectral sensors onboard the EOS platform, principally the Moderate Resolution Imaging Spectroradiometer (MODIS), and similar sensors launched by other countries (e.g., European Space Agency's Medium Resolution Imaging Spectrometer) have provided global observations for vegetation analysis over broad scales since the early 2000s. Advancements in hyperspectral and active radar and LIDAR sensors have been demonstrated with experimental sensors and hold promise for further enhancing the capabilities to observe invasive species, structural properties, and a host of other vegetation dynamics (13).

Since the early days of the space age, the number and types of sensors for studying terrestrial vegetation have multiplied many times over. Remote sensing observations are now indispensable in the Earth system scientist's toolbox. They provide access to otherwise inaccessible regions, consistency of coverage not available with ground measurements, and the ability to repeat measurements through time. Despite these advances, routine monitoring and operational use have not matched meteorological applications (13, 14). Many possibilities for applying remote sensing of terrestrial vegetation to sustainable management of ecosystems are currently unrealized (see Conclusions and Future Challenges, below).

This aricle reviews remote sensing of terrestrial vegetation in three major categories: understanding Earth system processes, assessing trends and consequences of human transformation of Earth's vegetation, and applications to ecosystem management. The reader may wish to consult (15–17) for basic principles of remote sensing. Although this review focuses on remote sensing of terrestrial vegetation, the strength of the approach is the opportunity to integrate remote sensing with models and empirical analyses to develop scientific underpinnings and applications for sustainable management of ecosystems.

Spatial resolution: the smallest separation between objects discernible by remote sensing data. Coarse resolution is grainy; fine resolution distinguishes finer-scale features on the ground

MODIS: Moderate Resolution Imaging Spectroradiometer

Active sensors: send out their own electromagnetic energy directed at the target to measure the returned radiation

Light Detection and Ranging (LIDAR): measures heights of objects and features on the ground by measuring the time delay between transmission of a pulse and detection of the reflected signal

Radio detection and ranging (radar): similar to LIDAR but transmits in longer wavelengths and can penetrate clouds

Remote sensing: acquisition of information about Earth's surface without direct contact, such as by sensors onboard an aircraft or satellite

fAPAR: fraction absorbed photosynthetically active radiation

REMOTE SENSING OF TERRESTRIAL VEGETATION IN EARTH SYSTEM PROCESSES

Earth system science views the atmosphere, biosphere, oceans, and solid earth as interacting components that exchange energy, water, and materials. Humans are a major component of the biosphere through modifying the spatial and temporal scales of these exchanges in the quest for food security and stability within a dynamic system. Because manipulative experiments on a global scale are not feasible, Earth system science relies on models to test sensitivities of the system to modified exchanges among the components. Earth system models range from simple conceptual models to complex, spatially explicit numerical simulations. General Circulation Models (GCMs), for instance, are complex models that test sensitivities of climate to accelerated addition of greenhouse gases to the atmosphere with fossil fuel combustion and other human activities (18).

Other types of Earth system models include biogeography models of the distribution of Earth's vegetation in response to climate [e.g., (19, 20)] and biogeochemical models of carbon and water cycle dynamics [e.g., (21–23)]. The distinction between these types of models is dissolving as GCMs increasingly incorporate complex ecological processes with advances in computing power and scientific understanding of vegetation's role in global processes (24).

Early GCMs assumed a homogeneous land surface and ignored the impact of heterogeneous vegetation and soil types on fluxes of energy, water, and momentum between the land surface and atmosphere. In the mid-1980s, the second generation of models coupled land surface schemes with GCMs. These schemes represented land-atmosphere fluxes using prescribed vegetation types (25) and remotely sensed estimates of the fraction of absorbed photosynthetically active radiation [fAPAR, the fraction of incoming solar radiation in the photosynthetically active radiation spectral region (400–700 nm) absorbed by plants] and leaf area index (the one-sided leaf area per unit of ground area) (26). Future generations led to dynamic vegetation models, which represent further complexity by incorporating vegetation's response to climate in terms of carbon and water exchanges, community composition, and vegetation structure (27–29). Although these advances have made major strides in capturing the complexities of the Earth system, major feedbacks are yet to be included, such as realistic representation of fire, human modifications of the land surface, and the role of biodiversity in land-atmosphere interactions.

Remote sensing of terrestrial vegetation has contributed in several ways to the advancements in Earth system models. First, input data to set boundary conditions in the models have been derived from remote sensing through global land-cover maps and biophysical fields such as leaf area index and fAPAR. Second, remote sensing has provided empirical, long-term data to increase understanding of ecological processes and their responses to climate change over large scales. Analysis of the 20-year record of the normalized difference vegetation index (NDVI) from the AVHRR, for example, suggests that productivity has increased with reduced cloudiness in the Amazon (30). Finally, remote sensing provides data on spatial and temporal distribution of processes not yet included in Earth system models, such as fire and other disturbances, and provides a basis for analyzing the importance of these processes in the Earth system (31).

The following sections briefly describe the major types of information provided by remote sensing that are directly relevant for Earth system science.

Vegetation Mapping for Climate Models

Traditional climate models require vegetation maps to assign boundary conditions, such as albedo and surface roughness, according to vegetation type. Albedos of coniferous forests, for example, range from 0.05 to 0.15, and grasslands have albedos of 0.16 to 0.26 (32). Taller surfaces are rougher than shorter surfaces and create turbulence, increasing the transfer of heat away from the surface.

NDVI: normalized difference vegetation index

Before remotely sensed data were available for mapping vegetation types, models relied on global compilations from atlases and ground-based surveys (33, 34). Pioneering research was carried out during the 1980s to map vegetation with remotely sensed data at continental scales, primarily with multitemporal data acquired by the AVHRR. Seasonal variations in photosynthetic activity (**Figure 1**) were used to map vegetation types in Africa (35) and South America (36). In the 1990s, the AVHRR data were used to map land cover globally at increasingly higher spatial resolution. The first global land-cover classification depicted broadly defined vegetation types at a coarse $1^\circ \times 1^\circ$ resolution (approximately 110 × 110 km at the equator) (37), followed by 8 × 8-km resolution (38), and 1 × 1-km resolution (39, 40). More recently launched sensors have provided globally comprehensive data to map vegetation types with greater accuracy with improved spectral and spatial resolutions of these sensors. Friedl et al. (41) have provided global land-cover maps using MODIS data at 1-km resolution and Bartholome & Belward (42) map land cover using SPOT VEGETATION data also at 1-km resolution. These maps characterize vegetation as broadly defined biome types. An alternative classification scheme maps anthropogenic biomes using categories such as rainfed villages and irrigated cropland (43). This latter approach explicitly recognizes the pervasive human presence in global ecosystems.

Land-cover maps categorize each grid cell according to a predefined classification system. Earth system models that use these maps have no option but to assign parameters according to this scheme. Another approach describes the landscape as continuous fields of vegetation characteristics (woody, grass, and bare) for a flexible characterization for application in models (44). Vegetation continuous fields have been derived globally from AVHRR data (45) and MODIS data (46). These data have been used in a range of models from global fire emissions

(47) to maps of plant functional types for land surface models (48).

Dynamic vegetation models that "grow" vegetation based on climatic variables within the GCM are independent of vegetation maps (27). These biogeographically oriented models, however, do not capture the considerable influence of human transformation of the land surface on global vegetation distributions (see section on Human Modification of Land Cover, below).

Passive sensors: detect naturally reflected (for visible wavelengths) or radiated (for thermal infrared wavelengths) energy from Earth's surface

Regional climate models are essential for assessing climate change impacts at more local scales than GCMs. Regional models are generally constructed to run for limited areas with higher spatial resolution (typically 50 km) and relatively short time periods (approximately 20 years). Similar to GCMs, regional climate models require boundary conditions that include land-cover type and time-varying leaf area index. Remote sensing is often the basis for deriving these input data sets (49).

Vegetation Dynamics in Biogeochemical Cycles

Biogeochemical models simulate exchanges of carbon, nitrogen, and water between soil, plants, water, and the atmosphere. These models are designed to address questions such as the sensitivity of carbon fluxes to fertilization of plant growth by atmospheric carbon, sources and sinks of nitrogen in ecosystems, and the response of crop yields to nutrient inputs. Coupling biogeochemical models with climate models has advanced representation of carbon cycle dynamics in the coupled Earth system. Cox et al. (29), for example, identified a crucial positive feedback between drier climates, reduced carbon uptake by vegetation, and enhanced concentrations of atmospheric carbon.

Carbon cycle. Remote sensing provides input data for biogeochemical models, particularly in relation to the carbon cycle. Biophysical properties of vegetation, such as leaf area index and fAPAR, are used to estimate rates of photosynthesis, evapotranspiration, and respiration. Several time-varying leaf area index and fAPAR products are now produced from various coarse-resolution sensors launched in the past 10 years [see Weiss et al. (50) for a comparison of these products]. A validation exercise comparing these products with ground measurements has assessed the accuracy of these products over a range of ground validation sites (51).

Several models rely on remote sensing data to estimate net primary production (NPP), a key attribute in the terrestrial carbon cycle (52). Estimates of daily gross primary production and annual NPP are now produced routinely for the global terrestrial surface at 1-km spatial resolution using a carbon cycle model and imagery from the MODIS sensor (53).

The long-term (since early 1980s) record from the AVHRR has been the backbone for assessing carbon dynamics on seasonal and annual scales. Red and near-infrared reflectances track changes in plant growth, most frequently using the NDVI (the difference over the sum of the two reflectance bands used in thousands of studies of terrestrial carbon dynamics). The NDVI record from the AVHRR data has undergone multiple reanalyses to correct for satellite drift, changes in platform, and other artifacts (54). The record has revealed, for example, that the length of the growing season has increased with warming in high latitudes (55), but drier summers might cancel out increased carbon uptake (56).

Spatially explicit estimates of biomass are also critical input data for studying the carbon cycle. One driving requirement for biomass data arises from the need to estimate carbon emissions from land-use change. These emissions are highly sensitive to the estimate of standing biomass prior to conversion (57). Optical data are insensitive to biomass above 50 to 80 Mg/ha (58), well below the biomass of tropical forests where land-use change is currently occurring most rapidly.

Active LIDAR and radar remote sensing systems are most suitable for mapping biomass and three-dimensional forest structure, particularly in tropical forests where clouds and high biomass present difficulties for passive sensors (59). LIDAR systems use laser altimeters to measure height and vertical structure (**Figure 2**), and radar systems penetrate clouds and heavy forest canopies with radio waves. To date, capabilities for LIDAR have been demonstrated with airborne sensors in specific locations (60–62). Radar data from airborne and satellite sensors have demonstrated their utility for mapping biomass (63–65). No global capabilities for measuring biomass and vegetation structure at repeated intervals currently exist for LIDAR data and are only beginning to become available for radar data. Satellite missions acquiring LIDAR and radar data have been recommended by the Earth science community (13).

Data from hyperspatial (very high-resolution) sensors, such as QuickBird and IKONOS, have become increasingly available through commercial providers. The ability to identify tree crowns enables forest structure and biomass estimates over small areas (66). The cost and data volume of hyperspatial imagery preclude its use over large areas, but imagery in a few locations provides calibration and validation of coarser-resolution imagery for studies extending over larger areas.

A key issue related to the carbon cycle and tropical vegetation is atmospheric carbon emissions from tropical deforestation, one of the most uncertain components of the global carbon budget. Estimates on the magnitude of the flux vary from 0.6 to 1.9 Pg C/year for the 1980s and 0.9 to 2.2 Pg C/year for the 1990s, or approximately 10% to 30% of fossil fuel emissions (67). The variability in estimates is due to uncertainties about biomass distributions and area deforested. The current policy debate about carbon credits for developing countries that reduce deforestation (68, 69) raises the imperative to improve deforestation and biomass mapping throughout the tropics (70, 71).

Nitrogen and water cycles. Observations in the red and near-infrared bands from multispectral sensors have been readily available over large areas for addressing terrestrial carbon dynamics. Analogous data for studying nitrogen and water cycling in terrestrial vegetation have not been available and are not as widely used in biogeochemical models. Water and nitrogen dynamics are intimately tied to the carbon cycle as limiting resources and have a range of environmental consequences. Changes to the nitrogen cycle from air pollution and agriculture affect vegetation productivity (and hence the carbon cycle), eutrophication of aquatic systems, atmospheric concentrations of the greenhouse gas nitrous oxide, and a host of human-health effects (72, 73).

Hyperspectral sensors (sometimes called imaging spectrometers) measure reflectances of hundreds of narrow spectral bands for each pixel, which enables mapping of canopy water content, vegetation stress, and nitrogen content (74). Research using hyperspectral sensors on aircrafts and satellites was established in the late 1980s (75). To date, these observations have not generally been integrated in Earth system models largely because routine, global observations and algorithms for converting observations into biophysical properties have not been available. Analysis from airborne hyperspectral sensors, such as the Airborne Visible/Infrared Imaging Spectrometer and the Hyperion sensor onboard the experimental EO-1 satellite, illustrates the enhanced information content for detecting leaf water and nitrogen content in case studies spanning many locations (76, 77). Hyperspectral analysis enables discrimination of plant pigments, leaf water and nutrient content, and in some cases species. These capabilities open possibilities for detailed vegetation mapping and for monitoring environmental stresses. Similar to LIDAR and radar sensors, a hyperspectral sensor on a satellite platform is a priority for the next decade of Earth observations (13).

Ecological Disturbances

Ecological disturbances are events resulting in sustained disruption of vegetation's function or structure over time periods greater than a single season. Disturbances such as fire, drought, insect outbreaks, and extreme weather events play major but poorly characterized roles in Earth system processes. Chambers et al. (78), for example, estimate that forest damage from Hurricane Katrina contributed 105 Tg C, or 50% to 140% of the net annual U.S. carbon sink in forest trees, to the atmosphere through enhanced respiration of coarse woody debris. As another example, the fires associated with the 1997–1998 El Niño in Indonesia were major contributors to the growth rate of carbon dioxide in the atmosphere in those years (79).

The episodic and unpredictable nature of disturbance events creates difficulties for incorporating these processes in Earth system models, even though their role in carbon cycling and other climate feedbacks is without question (80, 81). Remote sensing contributes toward identifying different types of disturbance and their effects on Earth system processes. This article describes remote sensing for identifying fire, insect damage, and drought as examples of the many types of disturbance.

Active fire and burn scars. Among the many types of disturbance, fire is the most amenable to remote sensing with sensors currently in orbit (82). Thermal infrared bands acquired by coarse-resolution sensors with at least daily observations detect actively burning fires based on the principle that thermal emissive power from fires is much more intense than the surrounding background. Many algorithms for active fire detection have been developed [see Ichoku et al. (83) for a comparison]. Active fire data show the enormous number of fires and the predominance of human activity as ignition sources, particularly in the tropics. Although active fire data is used in a number of operational applications, fires may easily be missed if they are not burning at the time of overpass or if they cannot be detected because of cloudy conditions or overlying vegetation.

Postfire burn scars provide additional information to active fire detection. Several algorithms and products identify burned area from multispectral coarse-resolution data, including GLOBSCAR (84), GBA2000 (85), and the MODIS burned-area product (86). Many researchers have identified burnt area at regional scales, for example in boreal ecosystems and savannas (87). The algorithms are generally based on temporal changes in infrared reflectance that are sensitive to changes in surface properties induced by fire. The ephemeral signal as regrowth gradually obscures burn scars makes these landscape features challenging to detect. To date, production of global, annual maps of burn scars remains a challenge. Burn scar detection often uses a combined approach based on frequency of active fire and burned area (88).

Insect damage. Disturbance from insect damage can alter carbon fluxes and decrease yields of economically valuable species. Research on mapping the severity and extent of insect damage has been conducted since the 1960s mainly using aerial photography. The Corn Blight Watch Experiment, designed in response to the devastating southern corn leaf blight fungus first noted in the southern and western United States in 1970, was one of the early applications of Landsat data (89). A number of remote sensing data sources have since been used to map insect damage, including multispectral high-resolution, multispectral coarse-resolution, and hyperspectral sensors. For example, Wulder et al. (90) map damage from mountain pine beetle in western North America and Tian et al. (91) map damage from the oriental migratory locust in China. The approaches generally rely on observations before and after outbreaks. The availability of cloud-free images at appropriate times is therefore critical.

Drought. Drought and its effects on crop yields is a key practical concern, particularly in parts of the world where agricultural production is severely limited by rainfall. In relation to Earth system science, water is often a limiting resource for plant growth and determines susceptibility to fire.

Vegetation water stress and soil moisture are drought indicators that are amenable to remote sensing. One approach for identifying water stress relies on remotely sensed surface temperature based on the notion that canopy temperature rises to dissipate sensible heat as vegetation becomes water stressed. Several methods have been used to estimate land surface temperature from thermal infrared data combined with energy balance models [see Jeyaseelan (92) for a review of drought monitoring methods].

Decreases in NDVI can also serve as a proxy for water stress, but this approach may not be applicable in tropical forests where saturation of NDVI may preclude multispectral approaches. Hyperspectral data have identified variations in canopy water in tropical forests (77). Water stress can also be inferred from changes in surface soil moisture observed with passive microwave sensing (13).

In summary, advancements in incorporating remote sensing of terrestrial vegetation in Earth system models have progressed furthest for those attributes derived from global, multispectral data. These attributes include vegetation maps and time-varying biophysical leaf area index and fAPAR used to model exchanges of carbon and water between plants and the atmosphere. Remotely sensed data on other biogeochemical transformations, such as nitrogen fluxes, are more amenable to hyperspectral analysis that has not been widely available over extensive areas. Their application in Earth system models has been more limited but holds significant potential if data become available. Likewise, remotely sensed data on episodic ecological disturbances provide a fruitful but unrealized integration of remote sensing data and Earth system models.

REMOTE SENSING OF INTERACTIONS BETWEEN HUMAN SOCIETIES AND VEGETATION

Human society and terrestrial vegetation have a complex relationship (**Figure 3**). On one hand, modification of vegetation through land-cover change is a fundamental basis for civilization in the provision of food crops, fiber, livestock; expansion of settlements for consolidation of economic activity; and movement of organisms through trade. On the other hand, this modification of the land surface potentially undermines these positive outcomes by interfering with a sustainable supply of ecosystem services (94). Altered habitats for keystone species, for example, can reduce productivity, nutrient cycling, disease regulation, and other ecological functions essential for maintaining production of species on which society depends (95, 96).

Understanding the causes and ramifications of these complex linkages has advanced over the past decade, although the field of land change science is still in its infancy (97–100). Remote sensing is a powerful tool to observe human modifications to terrestrial vegetation through conversion for agriculture and urban uses. Various types of remote sensing also provide information on the unintended consequences, including forest and dryland degradation, invasive species, biodiversity loss, and habitats for disease vectors. Remote sensing can also contribute to analyzing the feedbacks from these unintended consequences to human well-being through mapping of food security and poverty. Unraveling the linkages among demands from human societies, modification of the land surface, and functioning of terrestrial systems involves multiple approaches, including ecological field studies, social surveys, and repeated observations. Remote sensing contributes one piece to this larger picture and is the focus of the sections that follow.

Human Modification of Land Cover

Human societies modify land cover most directly by clearing vegetation for agriculture. Agricultural expansion has been the dominant force behind anthropogenic land-cover change since humans began to domesticate plant species 10,000 years ago. Currently, the remaining land area suitable for agricultural expansion is limited to South America and Africa. Increases in crop yield, necessary to keep pace with the growing appetite of an expanding population, have mainly occurred through intensification of agricultural production rather than

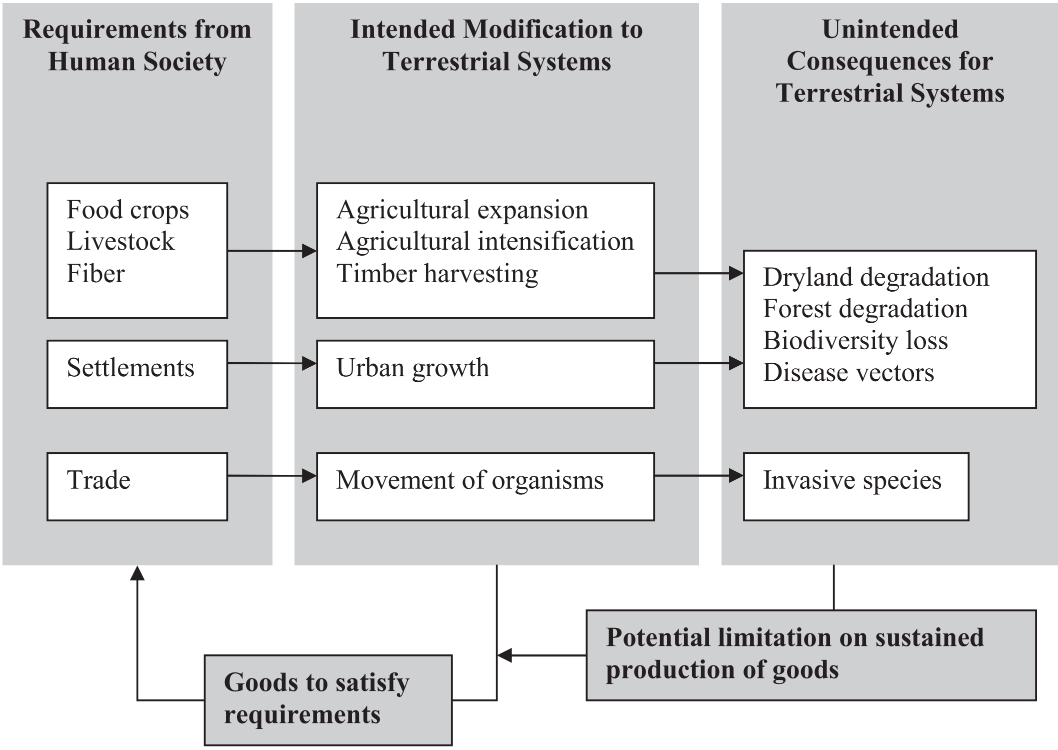

Figure 3

Linkages between human society and terrestrial vegetation. Remote sensing data contribute to understanding these linkages through mapping crop yields, land cover, vegetation productivity, urban patterns, and habitats.

extension into new areas over the past 50 years (101). This process is likely to continue into the future as land-use transitions continue on a path toward intensification (102). Urban areas cover only a small percentage of the terrestrial surface (3%–4%) but generate a far-reaching demand for ecosystem services. Rapid urbanization is occurring in nearly all parts of the world, particularly in Asia, and is poised to continue into the future. Remote sensing identifies trends and spatial distributions of these major types of human modification of land cover—agricultural expansion, agricultural intensification, and urban growth.

Agricultural expansion. Identifying land-cover change for local, regional, and global studies is one of the most frequent applications of terrestrial remote sensing. Most studies have focused on tropical forests for several reasons. Forest loss is relatively easily detected through multitemporal analysis of multispectral data from high-resolution (103) and medium- to coarse-resolution sensors (104–106). These studies focus on the tropics because the satellite era covers the time period in which tropical deforestation is extensive. Temperate deforestation occurred in North America and Europe prior to the satellite era.

Methods to identify deforestation from multitemporal, multispectral data are reasonably well established, ranging from visual interpretation to automated algorithms (71). Only a few tropical countries, however, have operational monitoring systems in place, i.e., Brazil (107) and India (108). Operational systems in other countries in the tropics are likely to develop with current policy interest in reduced deforestation as a climate mitigation strategy.

During the satellite record, many temperate countries have been in a phase of agricultural abandonment and forest regrowth following initial clearing (109). The regrowth serves as a sink for atmospheric carbon and alters habitats. High-resolution data are needed to identify the relatively patchy spatial scale and long temporal scale of this dynamic.

Remote sensing clearly cannot extend backward into historical time periods to capture temperate deforestation and other land transformations. Researchers have addressed this shortcoming by combining remote sensing-derived land cover for the current time period with historical census data to reconstruct spatially explicit data sets of land-cover change over the past several hundred years (3, 110).

Agricultural intensification. Increases in agricultural yield rather than expansion of land area accounts for the ability of food production to keep pace with population growth over the past several decades (111). Increases in agricultural inputs through irrigation, fertilizer, and high-yield crop types contribute to agricultural intensification. Several approaches to identify agricultural intensity, as opposed to agricultural expansion, have been developed.

Globally, irrigated area covers approximately 18% of the cultivated area and accounts for 40% of the world's food production (112). Data on the spatial distribution of irrigated agriculture provide the basis for assessing water demand, impacts of climate change on food production, and feedbacks from irrigated land surfaces to climate. Data sets have been derived from subnational irrigation statistics (112) and multispectral data (113). The approach relies on spatial differences in seasonality and greenness between irrigated and rainfed agriculture.

Another type of agricultural intensification is shift from land uses with low inputs of fertilizers and pesticides, such as pasture, to high-input land uses, such as mechanized cropland. Morton et al. (114) and Brown et al. (115) mapped land-use transitions from pasture to crop in the southern Amazon basin using multispectral data. The ability to identify postclearing land use helps quantify the emerging demand for agricultural commodities as a key driver for tropical deforestation.

Urban growth. Half of the world's population currently lives in urban areas. This proportion is expected to increase in the coming decades. Although urban areas cover only a few percent of the land surface, the concentration of economic activity creates a demand for resources far beyond their administrative boundaries.

Urban remote sensing provides information on many aspects of urban environments, including land-use patterns, growth, and heat island effects (116). Many studies use high-resolution sensors to document the extent, form, and growth of urban and periurban areas around the world (e.g., 117). Thermal bands on high-resolution sensors capture the urban heat island effect and provide possibilities to identify related health risks (118). Recent availability of hyperspatial and hyperspectral data has spawned new methods to identify urban features and building materials (119).

At the global scale, an annual time series of nighttime lights at approximately 1-km resolution derived from the Defense Meteorological Satellite Program (DMSP) Operational Linescan System maps the extent and expansion of urban areas globally (120). The DMSP was originally designed to collect global cloud imagery during daytime and nighttime and acquired data from 1992 to 2003. Calibration for varying light intensity in different regions confounds straightforward detection of urban growth with nighttime lights, but the time series is a cost-effective approach to indicate economic activity.

Forest and Dryland Degradation

Degradation of vegetation productivity is a major but poorly quantified consequence of unsustainable land-use practices (**Figure 3**). There is no standard definition of degradation. Generally, the term refers to the loss of vegetation's productivity and its ability to produce ecosystem services over a timescale that affects human livelihoods. Confusion often occurs between variability in productivity caused by climate variations and sustained loss caused by human use. In forest systems, unsustainable logging or overharvesting can lead to human-induced degradation. In drylands, human activities that lead to degradation include overgrazing and salinization from unsuitable irrigation practices. Remote sensing has contributed to identifying degradation, both in forest and dryland systems.

In forest systems, identifying reductions in canopy cover with remote sensing generally requires observations at frequent intervals because the spectral signature changes rapidly with regrowth. Hyperspatial data can observe tree crowns but cannot cover large areas. Spectral mixture models use high-resolution data to map fractional cover of green vegetation, nonphotosynthetically active vegetation, shade, and soil (**Figure 4**). The spatial patterns of these fractional components portray indicators of logging such as gaps, roads, and log decks (121, 122). An operational monitoring system, DETEX, is being developed for the Brazilian Amazon to monitor forest degradation as a complement to the deforestation monitoring system, PRODES (**http://www.obt.inpe.br/prodes/**). Applicability to mapping forest degradation from unsustainable logging in other forest systems has not been demonstrated.

Forest degradation by overexploitation of fuel wood and other nontimber forest products is extremely difficult to detect with remote sensing unless the degradation is intense. These activities potentially alter vegetation structure. LIDAR and radar data at high spatial resolution are potentially applicable but have not been demonstrated for this application.

Degradation in dryland systems (also ambiguously referred to as desertification) is a key development concern. Drylands cover about 41% of Earth's land surface and are home to about one third of the world's population. These populations lag far behind in human well-being and development indicators (123, 124). The key challenge for identifying degradation with remote sensing is to distinguish variability in climate-induced vegetation productivity from human-induced processes.

The long-term AVHRR record provides a critical base to determine causal relationships between drought, climate variability, and human land use in drylands. Tucker et al. (125) and Prince et al. (126) used associations between precipitation and remotely sensed vegetation productivity in the Sahel to suggest that desertification in the 1980s was less related to overgrazing and other human activities and more related to climate variability than previously thought. Recent extensions of the record provide further indication of the overwhelming effect of climate on productivity in the Sahel (127). Advances have also been made in identifying degradation with measures such as rain-use efficiency (ratio of NPP to rainfall) (128). A long time series of remote sensing observations is generally needed to identify trends in dryland degradation.

The global extent of dryland degradation is notoriously difficult to determine, and estimates vary widely (124). A compilation of remotely sensed and other data sources indicates that 10% of global drylands are degraded (129). This estimate is considerably lower than those that were based on expert opinion, research reports, and anecdotal accounts.

Invasive Species

Trade and transportation move organisms at rates and distances that far exceed ecological processes (**Figure 3**). When undesirable species spread from gardens or agricultural areas into wildlands, they can reproduce, displace native species, disrupt biodiversity and ecological processes, and increase susceptibility to fire (130). The ability to map and monitor invasive species underlies prospects for management and scientific advances in understanding how invasive species alter ecological functions and response to climate change.

Possibilities for mapping and monitoring invasive species have improved with the availability of hyperspectral data. High- and moderate-resolution multispectral sensors lack the required spatial and spectral resolution and are more suited to mapping at the community level. Aerial photography provides the necessary spatial resolution to discriminate species but lacks the spectral resolution. There has been some success in discriminating weed species from the background with hyperspectral data if they display different chemical composition, such as concentrations of chlorophyll, nitrogen, water, and canopy dry matter (74). This approach has been applied to map invasive species, for example, in semiarid environments in California (131), rainforests in Hawaii (132), and rangelands (133). The approaches use spectral libraries of the spectral response from different species to classify the vegetation.

Habitat Loss and Conservation of Biodiversity

Habitat loss is the main cause of the current massive decline in biodiversity, particularly in biodiversity-rich tropical forests. Multiple types of remote sensing data contribute to monitoring biodiversity indirectly and directly (134). The Gap Analysis Program maps diversity indirectly based on remotely sensed biophysical characteristics such as vegetation type and productivity. The characteristics serve as proxies to predict species distributions across large areas not feasible to survey on the ground (135). Multispectral analysis over large areas has also made it possible to determine that protected areas are generally effective in protecting habitat within their administrative boundaries, with the exception of some "paper parks" (136–138).

At a finer spectral and spatial scale, hyperspatial and hyperspectral sensors potentially identify tree crowns and individual species. Direct measures of biodiversity are becoming feasible with these sensors, as opposed to indirect measures that rely on remote sensing of biophysical parameters. LIDAR and radar capabilities to map vegetation structure can aid mapping of canopy habitat heterogeneity as a predictor of species abundance and richness (e.g., 139).

Disease Vectors

The same remote sensing approaches used for biodiversity mapping and monitoring apply to species involved in the transmission of disease. Mosquito vectors that transmit the *Plasmodium* parasites, for example, respond to climatic variability. A time series of vegetation greenness and soil moisture from multispectral sensors therefore serves as a proxy for malaria risk (140). Multitemporal data from high-resolution sensors provide critical information where disease vectors respond to habitat changes, such as the increase in biting rates of mosquitoes associated with deforestation in the Peruvian Amazon (141).

The 1993 outbreak of the hantavirus pulmonary syndrome (HPS) in the southwestern United States led to ecological monitoring and attempts to construct predictive models for future outbreaks using remote sensing data. El Niño-driven increases in late winter precipitation, combined with land-use patterns that favor habitat for the deer mouse reservoir species, increase human risk for HPS. A predictive model that accounts for all the complex factors such as landscape heterogeneity and microclimate difference rests on remote sensing observations over large areas (142).

The use of remote sensing for monitoring and mapping risk for human disease is only beginning to advance beyond a few case studies. Integration of remotely sensed data with ground-based ecological and social data is needed to develop reliable models and forecasting capabilities (143).

Poverty Mapping and Food Security

The negative repercussions of human modification of terrestrial vegetation often affect poor populations directly. Poverty constrains abilities to adapt to negative consequences or substitute resources by purchasing from elsewhere. For the rural poor practicing subsistence farming, climatic conditions and vegetation productivity are often correlated with access to food, water, and other resources.

Poverty mapping has generally relied on household surveys. Recent efforts have begun to incorporate remotely sensed ecological variables such as vegetation productivity to develop spatially explicit maps of poverty (143, 144). Elvidge et al. (145) developed a global approach to map poverty by combining population density with nighttime lights from DMSP based on the principle that brightness of lighting is correlated with economic activity.

These nascent efforts to map poverty based on remotely sensed ecological variables are promising to capture the spatial dimensions of poverty. Unraveling the multidimensional causes of poverty, in which ecological and climatic conditions are among many institutional, governance, and economic factors, requires melding social and ecological perspectives.

REMOTE SENSING TO MANAGE ECOSYSTEMS AND HUMAN WELL-BEING

Application of remote sensing for management of ecosystems and human welfare depends on a combination of sound scientific underpinning and routine access to observations. Some examples exist. The vast potential, however, is far from realized (143).

One example in which remote sensing data have been used operationally to support decision making is the Famine Early Warning Network (FEWS NET). The objective of FEWS NET is to provide information to decision makers as a component of responding to food crises (146). FEWS NET, run by the United States Agency for International Development since the 1980s, currently provides food security alerts in many countries of Africa, Central America, and Central Asia. Remote sensing has been one of the most successful tools to achieve this objective. NDVI values from coarse-resolution, multispectral sensors are compared with historical values to identify agricultural areas that are significantly less productive than in the past and in danger of crop failure. Remotely sensed NDVI is used in combination with rainfall estimates from meteorological satellites and ground stations to compute a water requirements satisfaction index for particular crops.

Remote sensing and biophysical data alone cannot provide all the necessary information to identify impending food crises. FEWS NET has incorporated a livelihood-based framework that relies on baseline studies of food access and income in different locations to determine impending food crises.

High-input mechanized production creates other opportunities for remote sensing to improve efficiency, maximize crop yields, and minimize costs and environmental effects from fertilizer and pesticide applications. Precision agriculture, or variable rate technology, identifies individual management units within an agricultural field (143). Tillage, seed variety, and rates of fertilizer and pesticide application can be adjusted for management units. Remotely sensed data can be used to identify management units and determine factors such as vegetation activity and areas prone to drought or weed infestation. If remote sensing data are available in real time, application rates can be adjusted to fit the conditions. The application of precision agriculture is limited by availability of high-resolution data, cost, and expertise.

Other examples of applications of remote sensing data to ecosystem management include drought monitoring in many countries (147) and active fire monitoring (148). These examples illustrate the use of remote sensing to provide information that can improve decision making. Availability of information, however, is only one component of improved decision making. Institutions and governance structures to effectively use the information are equally essential (149, 150). Moreover, remote sensing data is only useful when integrated with ground-based data on ecological and socioeconomic conditions.

CONCLUSIONS AND FUTURE CHALLENGES

Terrestrial vegetation plays a pivotal role in the Earth system by exchanging water, energy, and nutrients among organisms, the atmosphere, soils, and aquatic systems. Terrestrial vegetation is also a main interface between the Earth system and human society's use of resources. As a growing population becomes increasingly urbanized and adopts resource-intensive lifestyles, expansion on remaining arable land and intensified production on existing agricultural lands will continue. Conversion and intensification both alter exchanges in the system.

Earth system science aims to understand these interactions between components of the system, driven by the imperative to project ecological and social consequences. The synoptic view from remote sensing has transformed the perceived role of terrestrial vegetation in the system. Rather than a site-specific characteristic studied at the plot level, the global role of vegetation in carbon, water, and energy exchanges is now the norm in Earth system models.

Two satellite records have been the mainstay for remote sensing of terrestrial vegetation over the past several decades. One is the daily record beginning in the early 1980s of the visible, nearinfared, and thermal wavelengths from the AVHRR sensor. The original purpose for acquiring the data was meteorological applications, but the record has been invaluable for assessing ecological dynamics that occur over multiple temporal scales. Improved multispectral sensors launched in the early 2000s, such as MODIS and SPOT VEGETATION, are now expanding the time series. The record from the higher-resolution Landsat series has also been essential for studying terrestrial vegetation since the 1970s. Thousands of studies have used these data for studying land-cover change and habitat distributions. Many other sensors now acquire high-resolution data.

New capabilities are contributing to the use of remote sensing in studying Earth system processes and the influence of human activities. Research on hyperspectral data for analyzing nitrogen fluxes, water stress, and in some cases individual species is moving forward. Active LIDAR and radar sensors are providing information on the three-dimensional structure of vegetation, which is essential for assessing biomass, habitats, and effects of invasive species. The Earth science community has placed a priority on acquisition of global hyperspectral, LIDAR, and radar data at repeated intervals, in addition to maintaining the continuity of the long-term multispectral record.

Much has been achieved in integrating remote sensing of terrestrial vegetation in Earth system science over the past few decades, but many challenges remain. Remote sensing now provides observations at spatial resolutions orders of magnitude finer than the grid cell size of many Earth system models. Advances in computing power will continue to close the gap, but a mismatch remains in incorporating the fine-scale heterogeneity of ecological processes in Earth system models. In the temporal domain, representation of episodic and infrequent ecological events such as fire and drought are a next improvement for Earth system models. Incorporating anthropogenic land-cover change resulting from intermingled economic, political, and ecological factors is another challenge for Earth system models. It is unrealistic to attempt to accurately represent these complex processes in Earth system models, but the integration of observed anthropogenically driven land-cover changes in Earth system models is an achievable goal.

In addition to incorporating remote sensing of terrestrial vegetation in Earth system models, routine monitoring of human modifications that alter the availability of ecosystem services remains a challenge. Land cover is one well-recognized component because of its multipronged linkages with carbon storage, watershed protection, and other services. Other components include changing habitats for disease vectors, invasive species, and degradation of forest and dryland systems.

Operational ecosystem management for improved human well-being is a central goal for scientific investments to understand and monitor the role of terrestrial vegetation in the Earth system. Examples using terrestrial remote sensing for decision support exist, most prominently the FEWS NET. Access to terrestrial remote sensing will improve possibilities for management applications as one aspect of many institutional and governance factors involved in effective decisions for ecosystem management.

SUMMARY POINTS

1. Terrestrial vegetation plays pivotal roles in the coupled human-Earth system by transferring water, energy, and nutrients among the atmosphere, biota, and aquatic systems.
2. Terrestrial vegetation is a main interface between the Earth system and human societies, which clear vegetation, cultivate favorable species, and move organisms across long distances to obtain food, fiber, and other goods.
3. Remote sensing data have contributed over the past few decades to the transformation from local, plot-based studies to global-scale investigations of vegetation dynamics. Earth system models now routinely include dynamics of terrestrial vegetation.
4. Long-term, multispectral satellite observations since the early 1980s are the foundation for understanding dynamics of terrestrial vegetation and responses to climate and human land use.
5. Capabilities with active sensors to map nitrogen and water content and, in some cases, species distributions have been demonstrated in many case studies. These dynamics have not been applied at global and regional scales because routine observations have not been available.
6. Several examples illustrate the opportunity for remote sensing to contribute toward management of ecosystems and human well-being. Applications to poverty mapping, sustainable agriculture, human health, conservation, and other management goals are beginning to emerge.

FUTURE ISSUES

1. Challenges for the next generations of Earth system models include interactive and realistic representations of ecological disturbances and human land use.
2. Routine monitoring of terrestrial vegetation is yet to be achieved in spite of its relevance for the delivery of ecosystem services to human populations.
3. Observations from active- and finer-resolution sensors have a range of management applications. Realizing their potential involves scientific advances combined with improved access to observations.

DISCLOSURE STATEMENT

The author is not aware of any biases that might be perceived as affecting the objectivity of this review.

ACKNOWLEDGMENTS

The author is grateful to Doug Morton and Greg Asner for comments on a draft manuscript and Michelle Hofton for providing graphics. This article was written while I was at the University of Maryland, College Park campus.

LITERATURE CITED

1. Hassan R, Scholes RJ, Ash N, eds. 2005. *Ecosystems and Human Well-Being: Current Status and Trends, Volume 1*. Washington, DC: Island. 917 pp.
2. Asner GP, Elmore J, Olander L, Martin RE, Harris AT. 2004. Grazing systems, ecosystem responses, and global change. *Annu. Rev. Environ. Resour.* 29:261–99
3. Goldewijk CGM. 2001. Estimating global land use change over the past 300 years: the HYDE database. *Glob. Biogeochem. Cycles* 15(2):417–33
4. Foley JA, DeFries R, Asner GP, Barford CG, Bonan GB, et al. 2005. Global consequences of land use. *Science* 309:570–74
5. Plato. 2003. *The Timaeus and Critias of Plato*. Whitefish, MT: Kessinger. 218 pp.
6. Natl. Res. Counc. 2008. *Earth Observations from Space: The First 50 Years of Scientific Achievements*. Washington, DC: Natl. Acad. Press. 142 pp.
7. Rouse JW, Haas RH, Schell JA, Deering DW, Harlan JC. 1974. Monitoring the vernal advancement and retrogradation (greenwave effect) of natural vegetation. In *NASA/GSFC Type III Final Report*. Greenbelt, MD: NASA
8. Tucker CJ. 1979. Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sens. Environ.* 8(2):127–50
9. Tucker CJ, Fung IY, Keeling CD, Gammon R. 1986. The relationship of global green leaf biomass to atmospheric CO_2 concentrations. *Nature* 319:159–99
10. Goward SN, Masek JG. 2001. Landsat—30 years and counting. *Remote Sens. Environ.* 78(1):1–2
11. Markham BL, Storey JC, Williams DL, Irons JR. 2004. Landsat sensor performance: history and current status. *IEEE Trans. Geosci. Remote Sens.* 42(12):2691–94
12. Tilford S. 1984. Global habitability and Earth remote sensing. *Philos. Trans. R. Soc. A* 312(1519):115–18
13. Natl. Res. Counc. 2007. *Earth Science and Applications from Space: National Imperatives for the Next Decade and Beyond*. Washington, DC: Natl. Acad. Press. 456 pp.
14. Natl. Res. Counc. 2003. *Satellite Observations of the Earth's Environment: Accelerating the Transition of Research to Operations*. Washington, DC: Natl. Acad. Press. 182 pp.
15. Jensen JR. 2000. *Remote Sensing of the Environment: An Earth Resource Perspective*. Upper Saddle River, NJ: Prentice Hall. 544 pp.
16. Lillesand TM, Kiefer RW, Chipman JW. 2004. *Remote Sensing and Image Interpretation*. Hoboken, NJ: Wiley. 704 pp.
17. Liang S. 2004. *Quantitative Remote Sensing of Land Surfaces*. Hoboken, NJ: Wiley. 534 pp.
18. Steffen W, Jäger J, Carson DJ, Bradshaw C, eds. 2003. *Challenges of a Changing Earth. Global Change—The IGBP Ser*. Heidelburg, Ger: Springer-Verlag. 216 pp.
19. Sitch S, Smith B, Prentice IC, Arneth A, Bondeau A, et al. 2003. Evaluation of ecosystem dynamics, plant geography and terrestrial carbon cycling in the LPJ dynamic global vegetation model. *Glob. Change Biol.* 9(2):161–85
20. Bond WJ, Woodward FI, Midgley GF. 2005. The global distribution of ecosystems in a world without fire. *New Phytol.* 165(2):525–38
21. Bond-Lamberty B, Gower ST, Ahl DE, Thornton P. 2005. Reimplementation of the Biome-BGC model to simulate successional change. *Tree Physiol.* 25(4):413–24
22. Field CB, Randerson JT, Malmstrom CM. 1995. Global net primary production: combining ecology and remote sensing. *Remote Sens. Environ.* 51:74–88
23. Friedlingstein P, Cox PM, Betts RA, Bopp L, von Bloh W, et al. 2006. Climate-carbon cycle feedback analysis: results from the C4MIP model intercomparison. *J. Clim.* 19:3337–53
24. Sellers PJ, Dickinson RE, Randall DA, Betts AK, Hall FG, et al. 1997. Modeling the exchanges of energy, water, and carbon between continents and the atmosphere. *Science* 275:502–9
25. Dickinson RE. 1995. Land processes in climate models. *Remote Sens. Environ.* 51:27–38
26. Sellers PJ, Randall DA, Collatz GJ, Berry JA, Field CB, et al. 1996. A revised land surface parameterization (SiB2) for atmospheric GCMs. Part 1: Model formulation. *J. Clim.* 9:676–705
27. Bonan GB, Levis S, Sitch S, Vertenstein M, Oleson KW. 2003. A dynamic global vegetation model for use with climate models: concepts and description of simulated vegetation dynamics. *Glob. Change Biol.* 9(11):1543–66

28. Delire C, Foley JA, Thompson S. 2003. Evaluating the carbon cycle of a coupled atmosphere-biosphere model. *Glob. Biogeochem. Cycles* 17(1):1012. doi:10.1029/2002GB001870
29. Cox PM, Betts RA, Jones CD, Spall SA, Totterdell IJ. 2000. Acceleration of global warming due to carbon-cycle feedbacks in a coupled climate model. *Nature* 408:184–87
30. Nemani RR, Keeling CD, Hashimoto H, Jolly WM, Piper SC, et al. 2003. Climate-driven increases in global terrestrial net primary production from 1982 to 1999. *Science* 300:1560–63
31. van der Werf GR, Randerson JT, Collatz GJ, Giglio L, Kasibhatia PS, et al. 2004. Continental-scale partitioning of fire emissions during the 1997 to 2001 El Niño/La Niña period. *Science* 303:73–76
32. Bonan GB, DeFries R, Coe M, Ojima D. 2004. Land use and climate. In *Land Change Science*, ed. G Gutman, AC Janetos, CO Justice, EF Moran, JF Mustard, et al., pp. 301–14. Dordrecht, Neth.: Springer-Verlag
33. Matthews E. 1983. Global vegetation and land use: new high resolution data bases for climate studies. *J. Clim. Appl. Meteorol.* 22:474–87
34. Olson JS, Watts JA, Allison LJ. 1983. Carbon in Live Vegetation of Major World Ecosystems. *Oak Ridge Natl. Lab. Tech. Rep. ORNL 5862*, Oak Ridge, TN
35. Tucker CJ, Townshend JRG, Goff TE. 1985. African land-cover classification using satellite data. *Science* 227:369–75
36. Townshend JRG, Justice CO, Kalb VT. 1987. Characterization and classification of South American land cover types using satellite data. *Int. J. Remote Sens.* 8:1189–1207
37. DeFries RS, Townshend JRG. 1994. NDVI-derived land cover classification at global scales. *Int. J. Remote Sens.* 15(17):3567–86
38. DeFries RS, Hansen M, Townshend JRG, Sohlberg R. 1998. Global land cover classifications at 8 km spatial resolution: the use of training data derived from Landsat imagery in decision tree classifiers. *Int. J. Remote Sens.* 19(16):3141–68
39. Hansen M, DeFries RS, Townshend JRG, Sohlberg R. 2000. Global land cover classification at 1 km spatial resolution using a classification tree approach. *Int. J. Remote Sens.* 21(6):1331–64
40. Loveland TR, Reed BC, Brown JF, Ohlen DO, Zhu Z, et al. 2000. Development of a global land cover characteristics database and IGBP DISCover from 1 km AVHRR data. *Int. J. Remote Sens.* 21:1303–30
41. Friedl MA, McIver DK, Hodges JCF, Zhang XY, Muchoney D, et al. 2002. Global land cover mapping from MODIS: algorithms and early results. *Remote Sens. Environ.* 83(1–2):287–302
42. Bartholome E, Belward A. 2005. GLC2000: a new approach to global land cover mapping from Earth observation data. *Int. J. Remote Sens.* 26(9):1959–77
43. Ellis EC, Ramankutty N. 2008. Putting people in the map: anthropogenic biomes of the world. *Front. Ecol. Environ.* 6:doi: 10.1890/070062
44. DeFries RS, Field CB, Fung I, Justice CO, Matson PA, et al. 1995. Mapping the land surface for global atmosphere-biosphere models: toward continuous distributions of vegetation's functional properties. *J. Geophys. Res.* 100(D10):20867–82
45. DeFries R, Hansen M, Townshend J, Janetos A, Loveland T. 2000. A new global data set of percent tree cover derived from remote sensing. *Glob. Change Biol.* 6:247–54
46. Hansen MC, DeFries RS, Townshend J, Carroll M, Dimiceli C, et al. 2003. Global percent tree cover at a spatial resolution of 500 meters: first results of the MODIS vegetation continuous fields algorithm. *Earth Interact.* 7(10):1–15
47. Van der Werf GR, Randerson JT, Collatz GJ, Giglio L. 2003. Carbon emissions from fires in tropical and subtropical ecosystems. *Glob. Change Biol.* 9:547–62
48. Bonan GB, Oleson KW, Vertenstein M, Levis S, Zeng X, et al. 2002. The land surface climatology of the Community Land Model coupled to the NCAR Community Climate Model. *J. Clim.* 15:3123–49
49. Liang X-Z, Choi HI, Kunkel KE, Dai Y, Joseph E, et al. 2005. Surface boundary conditions for mesoscale regional climate models. *Earth Interact.* 9(Pap. 18):1–28
50. Weiss M, Baret F, Garrigues S, Lacaze R. 2007. LAI and fAPAR CYCLOPES global products derived from VEGETATION. Part 2: Validation and comparison with MODIS collection 4 products. *Remote Sens. Environ.* 110:317–31

51. Morisette J, Baret F, Privette JL, Myneni R, Nickeson JE, et al. 2006. Validation of global moderate-resolution LAI products: a framework proposed within the CEOS land product validation subgroup. *IEEE Geosci. Remote Sens. Lett.* 44:1804–17
52. Turner DP, Ollinger SV, Kimball JS. 2004. Integrating remote sensing and ecosystem process models for landscape- to regional-scale analysis of the carbon cycle. *BioScience* 54(6):573–84
53. Running S, Nemani RR, Heinsch FA, Zhao M, Reeves M, et al. 2004. A continuous satellite-derived measure of global terrestrial primary production. *BioScience* 54:547–60
54. Brown ME, Pinzon JE, Didan K, Morisette J, Tucker CJ. 2006. Evaluation of the consistency of long-term NDVI time series derived from AVHRR, SPOT-Vegetation, SeaWiFS, MODIS, and Landsat ETM+ sensors. *IEEE Trans. Geosci. Remote Sens.* 44(7):1787–93
55. Myneni R, Keeling CD, Tucker CJ, Asrar G, Nemani RR. 1997. Increased plant growth in the northern high latitudes from 1981 to 1991. *Nature* 386(6626):698–702
56. Angert A, Biraud S, Bonfils C, Henning CC, Buermann W, et al. 2005. Drier summers cancel out the CO_2 uptake enhancement induced by warmer springs. *Proc. Natl. Acad. Sci. USA* 102(31):10823–27
57. Houghton RA. 2005. Aboveground forest biomass and the global carbon balance. *Glob. Change Biol.* 11:945–58
58. Dong J, Kaufmann RK, Myneni RB, Tucker CJ, Kauppi PE, et al. 2003. Remote sensing estimates of boreal and temperate forest woody biomass: carbon pools, sources, and sinks. *Remote Sens. Environ.* 84:393–410
59. Chambers JQ, Asner GP, Morton D, Anderson LO, Saatchi S, et al. 2007. Regional ecosystem structure and function: ecological insights from remote sensing of tropical forests. *Trends Ecol. Evol.* 22(8):414–23
60. Hurtt GC, Dubayah R, Drake JB, Moorcroft PR, Pacala SW, et al. 2004. Beyond potential vegetation: combining LIDAR data and a height-structured model for carbon studies. *Ecol. Appl.* 14(3):873–83
61. Lefsky MA, Turner DP, Guzy M, Cohen WB. 2005. Combining LIDAR estimates of aboveground biomass and Landsat estimates of stand age for spatially extensive validation of modeled forest productivity. *Remote Sens. Environ.* 94(4):549–58
62. Weishampel JF, Blair JB, Knox RG, Dubayah R, Clark DB. 2000. Volumetric LIDAR return patterns from an old-growth tropical rainforest canopy. *Int. J. Remote Sens.* 21:409–15
63. Saatchi S, Houghton RA, Alvala RC, Soares J, Yu Y. 2006. Distribution of aboveground live biomass in the Amazon basin. *Glob. Change Biol.* 13(4):816–37
64. De Grandi G, Mayaux P, Rauste Y, Rosenqvist A, Simard M, et al. 2000. The global rain forest mapping project JERS-1 radar mosaic of tropical Africa: development and product characteristics. *IEEE Trans. Geosci. Remote Sens.* 38(5):2218–33
65. Rauste Y. 2005. Multi-temporal JERS SAR data in boreal forest biomass mapping. *Remote Sens. Environ.* 97:263–75
66. Palace M, Keller M, Asner GP, Hagen S, Braswell BH. 2008. Amazon forest structure from IKONOS satellite data and the automated characterization of forest canopy properties. *Biotropica.* 40(2):141–50
67. Denman KL, Brasseur G, Chidthaisong A, Ciais P, Cox PM, et al. 2007. Coupling between changes in the climate system and biogeochemistry. In *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. S Solomon, D Qin, M Manning, Z Chen, M Marquis, et al., pp. 499–587. Cambridge, UK/New York: Cambridge Univ. Press
68. Gullison RE, Frumhoff PC, Canadell JG, Field CB, Nepstad DC, et al. 2007. Tropical forests and climate policy. *Science* 316:985–86
69. Santilli M, Moutinho P, Schwartzman S, Nepstad DC, Curran LM, et al. 2005. Tropical deforestation and the Kyoto Protocol: an editorial essay. *Clim. Change* 71:267–76
70. Achard F, DeFries R, Eva H, Hansen M, Mayaux P, et al. 2007. Pan-tropical monitoring of deforestation. *Environ. Res. Lett.* 2. doi:10.1088/1748-9326/2/4/045022
71. DeFries R, Achard F, Brown F, Herold M, Murdiyarso D, et al. 2007. Reducing greenhouse gas emissions from deforestation in developing countries: considerations for monitoring and measuring. *Environ. Sci. Policy* 10(4):385–94
72. Matson PA, Cohse KA, Hall SJ. 2002. The globalization of nitrogen deposition: consequences for terrestrial ecosystems. *Ambio* 31:113–19

73. Townsend A, Howarth R, Bazzaz FA, Booth MS, Cleveland CC, et al. 2003. Human health effects of a changing nitrogen cycle. *Front. Ecol. Environ.* 1(5):240–46
74. Ustin SL, Roberts DA, Gamon JA, Asner GP, Green RO. 2004. Using imaging spectroscopy to study ecosystem processes and properties. *BioScience* 54(6):523–34
75. Wessman CA, Aber J, Peterson DL, Melillo J. 1988. Remote sensing of canopy chemistry and nitrogen cycling in temperate forest ecosystems. *Nature* 335:154–56
76. Wulder MA, Hall RJ, Coops NC, Franklin SE. 1998. Optical remote-sensing techniques for the assessment of forest inventory and biophysical parameters. *Prog. Phys. Geogr.* 22:449–76
77. Asner GP, Nepstad DC, Cardinot G, Ray D. 2004. Drought stress and carbon uptake in an Amazon forest measured with spaceborne imaging spectroscopy. *Proc. Natl. Acad. Sci. USA* 101:6039–44
78. Chambers JQ, Fisher JI, Zeng H, Chapman EL, Baker DB, et al. 2008. Hurricane Katrina's carbon footprint on U.S. Gulf Coast forests. *Science* 318:1107
79. Page S, Siegert F, Rieley JO, Boehm HD, Jaya A, et al. 2002. The amount of carbon released from peat and forest fires in Indonesia. *Nature* 420(6911):29–30
80. Potter C, Tan P-N, Steinbach M, Klooster S, Kumar V, et al. 2003. Major disturbance events in terrestrial ecosystems detected using global satellite data sets. *Glob. Change Biol.* 9(7):1005–21
81. Randerson JT, Liu H, Flanner MG, Chambers SD, Jin Y, et al. 2006. The impact of boreal forest fire on climate warming. *Science* 314:1130–32
82. Lentile LB, Holden ZA, Smith AMS, Falkowski MJ, Hudak AT, et al. 2006. Remote sensing techniques to assess active fire characteristics and postfire effects. *Int. J. Wildl. Fire* 15:319–45
83. Ichoku C, Kaufman YJ, Gigio L, Li Z, Fraser RH, et al. 2003. Comparative analysis of daytime fire detection algorithms, using AVHRR data for the 1995 fire season in Canada: perspectives for MODIS. *Int. J. Remote Sens.* 24:1669–90
84. Simon M, Plummer S, Fierens F, Hoelzemann JJ, Arino O. 2004. Burnt area detection at global scale using ATSR-2: the GLOBSCAR products and their qualification. *J. Geophys. Res. Atmos.* 109:D14S02
85. Tansey K, Gregoire J-M, Stropiana D, Sousa A, Silva J, et al. 2004. Vegetation burning in the year 2000: global burned area estimates from SPOT VEGETATION data. *J. Geohphys. Res. Atmos.* 109:D14S03
86. Roy DP, Jin Y, Lewis PE, Justice CO. 2005. Prototyping a global algorithm for systematic fire-affected area mapping using MODIS time-series data. *Remote Sens. Environ.* 97:137–62
87. Loboda T, O'Neal KJ, Csiszar I. 2007. Regionally adaptable dNBR-based algorithm for burned area mappng from MODIS data. *Remote Sens. Environ.* 109(4):429–42
88. Giglio L, Van der Werf GR, Randerson JT, Collatz GJ, Kasibhatla P. 2006. Global estimation of burned area using MODIS active fire observations. *Atmos. Chem. Phys.* 6:957–74
89. MacDonald RB, Allen RD, Bauer ME, Clifton JW, Frickson JD, et al. 1972. Results of the 1971 Corn Blight Watch experiment. *Proc. 8th Int. Symp. Remote Sens. Environ., Ann Arbor*, pp. 157–90. Ann Arbor, MI: Environ. Res. Inst. Mich.
90. Wulder MA, Dymond CC, White JC, Leckie DG, Carroll AL. 2006. Surveying mountain pine beetle damage of forests: a review of remote sensing opportunities. *For. Ecol. Manag.* 221:27–41
91. Tian HD, Ji R, Xie BY, Li XH, Li DM. 2007. Using multi-temporal Landsat ETM+ data to monitor the plague of oriental migratory locust. *Int. J. Remote Sens.* 26:629–34
92. Jeyaseelan AT. 2003. Droughts and floods assessment and monitoring using remote sensing and GIS. In *Satellite Remote Sensing and GIS Applications in Agricultural Meteorology*. Proc. Train. Workshop, 7–11 July, Dehra Dun, India. Geneva, Switz: World Meteorol. Org.
93. Deleted in proof
94. Millenn. Ecosyst. Assess. 2005. *Ecosystems and Human Well-Being: Our Human Planet*. Washington, DC: Island. 109 pp.
95. Hooper DU, Chapin FSI, Ewel JJ, Hector A, Inchausti P, et al. 2005. Effects of biodiversity on ecosystem functioning: a consensus of current knowledge. *Ecol. Monogr.* 75(1):3–35
96. Diaz S, Lavorel S, de Bello F, Quetier F, Grigullis K, et al. 2007. Incorporating plant functional diversity effects in ecosystem service assessments. *Proc. Natl. Acad. Sci. USA* 104(52):20684–89
97. DeFries R, Asner GP, Houghton RA, eds. 2004. *Ecosystems and Land Use Change*. Geophys. Monogr. Ser. Vol. 153. Washington, DC: Am. Geophys. Union. 309 pp.

98. Gutman G, Janetos J, Justice CO, Moran EF, Mustard J, et al., eds. 2004. *Land Change Science: Observing, Monitoring, and Understanding Trajectories of Change on the Earth's Surface*. New York: Springer
99. Lambin EF, Geist HJ, eds. 2006. *Land-Use and Land-Cover Change: Local Processes and Global Impacts*. Berlin: Springer-Verlag. 222 pp.
100. Rindfuss RR, Walsh SJ, Turner BL II, Fox J, Mishra V. 2004. Developing a science of land change: challenges and methodological issues. *Proc. Natl. Acad. Sci. USA* 101(39):13976–81
101. Mooney HA, Cropper A, Reid WV. 2005. Confronting the human dilemma: How can ecosystems provide sustainable services to benefit society? *Nature* 434:561–62
102. DeFries R, Foley J, Asner GP. 2004. Land use choices: balancing human needs and ecosystem function. *Front. Ecol. Environ.* 2(5):249–57
103. Achard F, Eva H, Stibig HJ, Mayaux P, Gallego J, et al. 2002. Determination of deforestation rates of the world's humid tropical forests. *Science* 297:999–1002
104. Hansen M, DeFries R. 2004. Detecting long term forest change using continuous fields of tree cover maps from 8 km AVHRR data for the years 1982–1999. *Ecosystems* 7(7):695–716
105. Morton D, DeFries R, Shimabukuro Y, Anderson L, Espirito-Santo F, et al. 2005. Rapid assessment of annual deforestation in the Brazilian Amazon using MODIS data. *Earth Interact.* 9(8):1–22
106. Langner A, Miettinen J, Siegert F. 2007. Land cover change 2002–2005 in Borneo and the role of fire derived from MODIS imagery. *Glob. Change Biol.* 13:1–12
107. INPE. 2005. *Monitoramento da Floresta Amazônica Brasileira por Satelite, Projeto PRODES*. **http://www.obt.inpe.br/prodes/index.html**
108. For. Surv. India. 2004. State of Forest Report 2003. *Ministry of Environment and Forests*. Dehra Dun, India: Gov. India
109. Rudel TK, Coomes OT, Moran EF, Achard F, Angelsen A, et al. 2005. Forest transitions: towards a global understanding of land use change. *Glob. Environ. Change* 15:23–31
110. Ramankutty N, Foley J. 1999. Estimating historical changes in global land cover: croplands from 1700 to 1992. *Glob. Biogeochem. Cycles* 13(4):997–1027
111. Wood S, Ehui S. 2005. Food. See Ref. 1, pp. 209–41
112. Siebert S, Doll P, Hoogeveen J, Faures J-M, Frenken K, et al. 2005. Development and validation of the global map of irrigation areas. *Hydrol. Earth Syst. Sci.* 9:535–47
113. Biggs TW, Thenkabail PS, Gumma MK, Scott CA, Parthasaradhi GR, Turral H. 2006. Irrigated area mapping in heterogeneous landscapes with MODIS time series, ground truth and census data, Krishna Basin, India. *Int. J. Remote Sens.* 10:4245–66
114. Morton D, DeFries R, Shimabukuro Y, Anderson L, Arai E, et al. 2006. Cropland expansion changes deforestation dynamics in the southern Brazilian Amazon. *Proc. Natl. Acad. Sci. USA* 103(39):14637–41
115. Brown JC, Jepson W, Price KP. 2004. Expansion of mechanized agriculture and land-cover change in southern Rondonia, Brazil. *J. Lat. Am. Geogr.* 3(1):96–102
116. Weng Q, Quattrochi DA, eds. 2007. *Urban Remote Sensing*. Boca Raton, FL: CRC Press. 412 pp.
117. Schneider A, Woodcock CE. 2008. Compact, dispersed, fragmented, extensive? A comparison of urban growth in 25 global cities using remotely sensed data, pattern metrics and census information. *Urban Stud.* 45(3):659–92
118. Lo CP, Quattrochi DA. 2003. Land-use and land-cover change, urban heat island phenomenon, and health implications: a remote sensing approach. *Photogramm. Eng. Remote Sens.* 69(9):1053–63
119. Herold M, Roberts D, Gardner ME, Dennison PE. 2004. Spectrometry for urban area remote sensing—Development and analysis of a spectral library from 350 to 2400 nm. *Remote Sens. Environ.* 91(3–4):304–19
120. Small C, Pozzi F, Elvidge CD. 2005. Spatial analysis of global urban extent from DMSP-OLS night lights. *Remote Sens. Environ.* 96:277–91
121. Asner GP, Knapp DE, Broadbent E, Oliviera P, Keller M, et al. 2005. Selective logging in the Brazilian Amazon. *Science* 310:480–82
122. Souza CM Jr, Roberts D, Cochrane MA. 2005. Combining spectral and spatial information to map canopy damages from selective logging and forest fires. *Remote Sens. Environ.* 98:329–43
123. Reynolds JF, Smith DMS, Lambin E, Turner BL II, Mortimore M, et al. 2007. Global desertification: building a science for dryland development. *Science* 316:847–51

124. Safriel U, Adeel Z. 2005. Dryland systems. See Ref. 1, pp. 623–62
125. Tucker CJ, Dregne HE, Newcomb WW. 1991. Expansion and contraction of the Sahara Desert from 1980 to 1990. *Science* 253:299–301
126. Prince S, Brown de Colstoun E, Kravitz L. 1998. Evidence from rain use efficiencies does not support extensive Sahelian desertification. *Glob. Change Biol.* 4:359–74
127. Anyamba A, Tucker CJ. 2005. Analysis of Sahelian vegetation dynamics using NOAA-AVHRR NDVI data from 1981–2003. *J. Arid Environ.* 63:596–614
128. Wessels KJ, Prince SD, Malherbe J, Small J, Frost PE, et al. 2007. Can human-induced land degradation be distinguished from the effects of rainfall variability? A case study in South Africa. *J. Arid Environ.* 68(2):271–97
129. Lepers E, Lambin EF, Janetos AC, DeFries R, Achard F, et al. 2005. A synthesis of rapid land-cover change information for the 1981–2000 period. *BioScience* 55(2):115–24
130. Bradley AB, Houghton RA, Mustard J, Hamburg SP. 2006. Invasive grass reduces aboveground carbon stocks in shrublands of the western US. *Glob. Change Biol.* 12:1815–22
131. Underwood E, Ustin SL, DiPietro D. 2003. Mapping nonnative plants using hyperspectral imagery. *Remote Sens. Environ.* 86:150–61
132. Asner GP, Vitousek PM. 2005. Remote analysis of biological invasion and biogeochemical change. *Proc. Natl. Acad. Sci. USA* 102(1–2):4383–86
133. Lawrence RL, Wood SD, Sheley RL. 2006. Mapping invasive plants using hyperspectral imagery and Breiman Cutler classifications (RandomForest). *Remote Sens. Environ.* 100:356–62
134. Turner W, Spector S, Gardiner N, Fladeland M, Sterling E, et al. 2003. Remote sensing and biodiversity science and conservation. *Trends Ecol. Evol.* 18(6):306–14
135. Jennings MD. 2000. Gap analysis: concepts, methods, and recent results. *Landsc. Ecol.* 15(1):5–20
136. Oliveira PJ, Asner GP, Knapp DE, Almeyda A, Galvan-Gildemeister R, et al. 2007. Land-use allocation protects the Peruvian Amazon. *Science* 317(5842):1233–36
137. DeFries R, Hansen AJ, Newton AC, Hansen MC. 2005. Increasing isolation of protected areas in tropical forests over the past twenty years. *Ecol. Appl.* 15(1):19–26
138. Nepstad DC, Schwartzman S, Bamberger B, Santilli M, Ray D, et al. 2006. Inhibition of Amazon deforestation and fire by parks and indigenous lands. *Conserv. Biol.* 20(1):65–73
139. Goetz SJ, Steinberg D, Dubayah R, Blair B. 2007. Laser remote sensing of canopy habitat heterogeneity as a predictor of bird species richness in an eastern temperate forest, USA. *Remote Sens. Environ.* 108:254–63
140. Rogers DJ, Randolph SE, Snow RW, Hay SI. 2002. Satellite imagery in the study and forecast of malaria. *Nature* 415:710–15
141. Vittor A, Gilman R, Tielsch J, Glass G, Shields T, et al. 2006. The effect of deforestation on the human-biting rate of *Anopheles darlingi*, the primary vector of falciparum malaria in the Peruvian Amazon. *Am. J. Trop. Med. Hyg.* 74(1):3–11
142. Yates TL, Mills JN, Parmenter CA, Ksiazek TG, Parmenter RR, et al. 2002. The ecology and evolutionary history of an emergent disease: hantavirus pulmonary syndrome. *BioScience* 52:989–98
143. Natl. Res. Counc. 2006. *Contributions of Land Remote Sensing for Decisions About Food Security and Human Health: Workshop Report*. Washington, DC: Natl. Acad. Press. 112 pp.
144. Hyman G, Larrea C, Farrow A. 2005. Methods, results and policy implications of poverty and food secutiry mapping assessments. *Food Policy* 30(5–6):453–60
145. Salvatore M, Pozzi F, Ataman E, Huddleston B, Bloise M. 2005. *Mapping global urban and rural population distributions*. Environ. Nat. Resour. Work. Pap. 24, Food Agric. Organ. Rome, Italy. 24 pp.
146. Verdin J, Funk C, Senay G, Choularton R. 3005. Climate science and famine early warning. *Philos. Trans. R. Soc. B* 360:2155–68
147. Sivakumar MVK, Roy PS, Harmsen K, Saha SK, eds. 2004. *Satellite Remote Sensing and GIS Applications in Agricultural Meteorology AGM-8, WMO/TD No. 1182*. Geneva, Switz.: World Meteorol. Org.
148. Davies D, Kumar S, Descloitres J. 2004. Use of MODIS near-real-time satellite data: global fire monitoring. *GIM Int.* 18(4):41–43
149. Natl. Res. Counc. 2002. *Transforming Remote Sensing Data into Information and Applications*. Washington, DC: Natl. Acad. Press.
150. Natl. Res. Counc. 2003. *Using Remote Sensing in State and Local Government.* Washington, DC: Natl. Acad. Press.

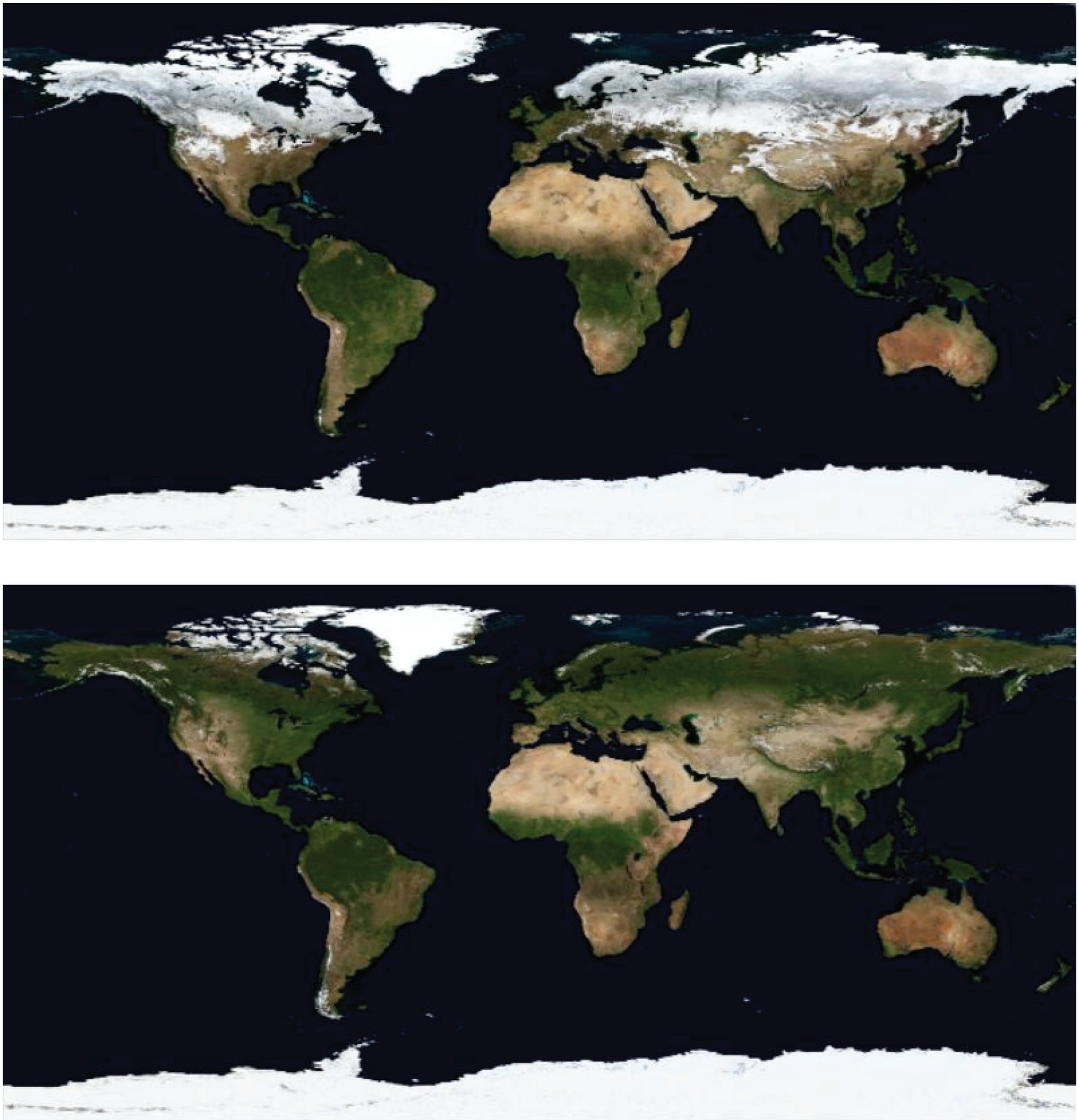

Figure 1

MODIS-derived 500-m true-color global data set for January (*top*) and July (*bottom*). From **http://onearth.jpl.nasa.gov/**.

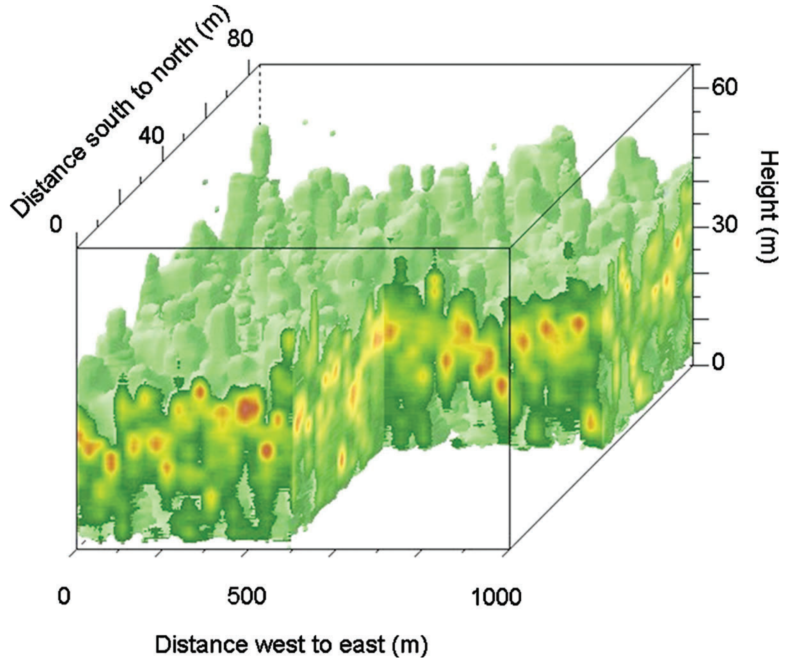

Figure 2

Volumetric renderings of canopy structure of an approximately 1-km^2 area of the La Selva Biological Research Station, Costa Rica. Data were collected using NASA's Laser Vegetation Imaging Sensor (LVIS) (62) in March 1998. LVIS is a medium footprint (25-m wide), medium altitude (10-km altitude) waveform-recording laser altimeter system. Color is intensity of the LIDAR return at each height (*green* is lowest, *red* is highest). Graphic courtesy of J.F. Weishampele.

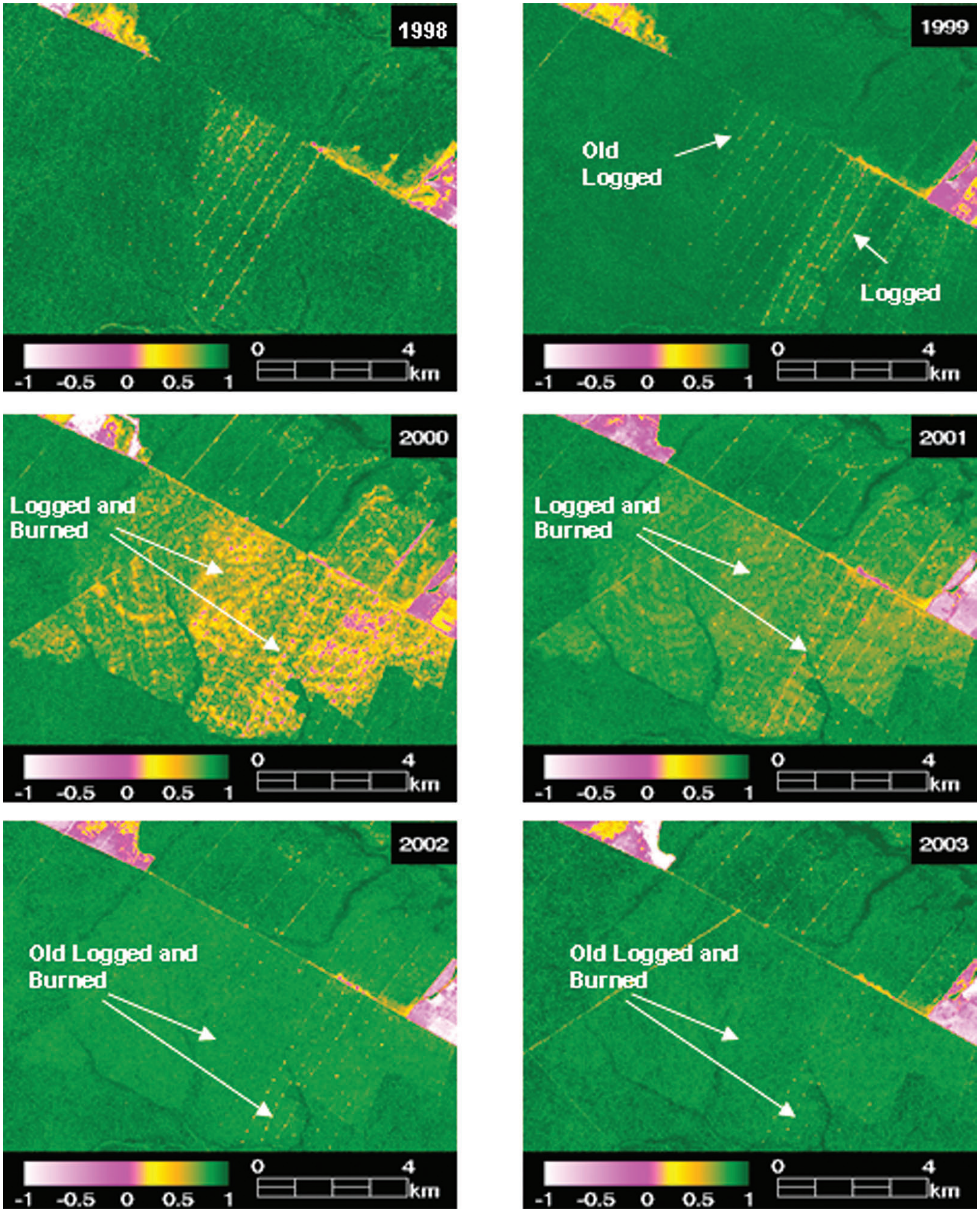

Figure 4

Annual change from 1998 to 2003 in forest degradation from selective logging and burning in the Sinop region, Mato Grosso state, Brazil. Data from Landsat 5 (bands 5, 4, and 3). Color bar indicates subpixel fraction of shade-normalized green vegetation (–1 is 0% green vegetation, +1 is 100% green vegetation) (122). Graphic courtesy of Carlos Souza, Jr.

Annual Review of Environment and Resources

Volume 33, 2008

Contents

III. Management, Guidance, and Governance of Resources and Environment

IV. Integrative Themes

Indexes

Errata

An online log of corrections to *Annual Review of Environment and Resources* articles may be found at http://environ.annualreviews.org