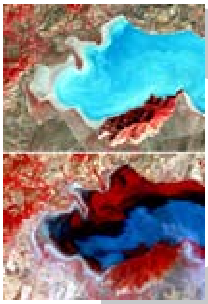
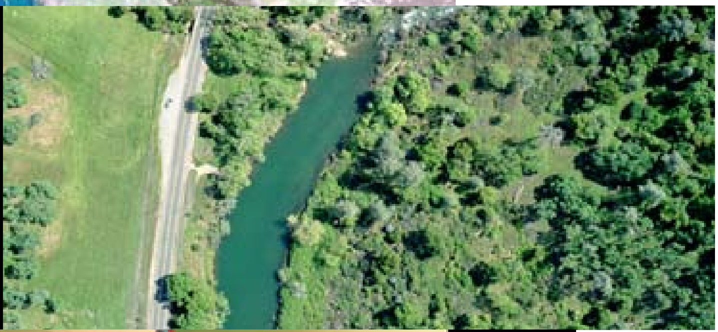
Secretariat
of the Convention on
Biological Diversity

CBD Technical Series No. 32



SOURCEBOOK ON REMOTE SENSING AND BIODIVERSITY INDICATORS

Prepared by the NASA-NGO Biodiversity Working Group and UNEP-WCMC to support implementation of the Convention on Biological Diversity



Edited by Holly Strand, Robert Höft, James Strittholt, Lera Miles, Ned Horning, Eugene Fosnight and Woody Turner

Sourcebook on Remote Sensing and Biodiversity Indicators

Prepared by the NASA-NGO Biodiversity Working Group and UNEP-WCMC to support implementation of the Convention on Biological Diversity

Edited by
Holly Strand, Robert Höft, James Strittholt, Ned Horning, Lera Miles, Eugene Fosnight and Woody Turner

Published jointly by the Secretariat of the Convention on Biological Diversity, the NASA-NGO Biodiversity Working Group, and the World Conservation Monitoring Centre of the United Nations Environment Programme. ISBN: 92-9225-072-8

Citation:
Strand, H., Höft, R., Strittholt, J., Miles, L., Horning, N., Fosnight, E., Turner, W., eds. (2007). Sourcebook on Remote Sensing and Biodiversity Indicators. Secretariat of the Convention on Biological Diversity, Montreal, Technical Series no. 32, 203 pages

Typesetting: Black Eye Design

For further information, please contact
Secretariat of the Convention on Biological Diversity
World Trade Centre
413 St. Jacques Street, Suite 800
Montreal, Quebec, Canada H2Y 1N9
Phone: 1(514) 288 2220
Fax: 1 (514) 288 6588
E-mail: secretariat@biodiv.int
Website: www.cbd.int

Contributing authors (in alphabetical order):
Soumitri Das, Karl Didier, Jessica Forest, Eugene Fosnight, Ned Gardiner, Peter Herkenrath, Robert Höft, Ned Horning, Colby Loucks, Valerie Kapos, Peter Leimgruber, Ian May, Lera Miles, Thomas Mueller, Corinna Ravilious, Eric Sanderson, Marc Steininger, Holly Strand, James Strittholt, Janice Thompson, Ben White, Emma Underwood, Susan Ustin

This work was made possible by NASA Grant NNG04GP10G "Decision Support for the Convention on Biological Diversity 2010 Goal."

Special thanks to Woody Turner, Program Scientist, NASA's Office of Earth Science. He represents a critical link between remote sensing scientists and biodiversity scientists and professionals.

The following people supported this project in many different but important ways:
Jo Mulongoy (CBD Secretariat), David Cooper (CBD Secretariat), Jerry Harrison (UNEP-WCMC), Charles Hawkins (Utah State University), Lena Hawkins, Chris Luecke (Utah State University), Alexander de Sherbinin (CIESIN), Scott Bergen (WCS), Leo Sotomayor (TNC), Jamie Ervin (TNC), Taylor Ricketts (WWF), Sheila O'Connor (WWF), Andrew Balmford (University of Cambridge), Patty Kuhns and Jennifer Bowman.

Foreword

Humankind is facing unprecedented threats caused by our unsustainable use of Earth's natural resources. Increasingly, we are realizing the finite capacity of our globe to absorb the consequences of our activities: ongoing degradation and loss of natural ecosystems and dependent species; overuse of resources; pollution of water, land and the atmosphere; and modifications in atmospheric composition leading to climate change with all its consequences. The universally agreed target to achieve a significant reduction in the rate of loss of biodiversity by the year 2010 has provided cohesion to the efforts of Governments, non-governmental organizations, private sector partners, and civil society alike to collaboratively reduce the size of our ecological footprint.

Technological advances, refined methodologies and growing databases make our systems for monitoring biodiversity increasingly effective. As this document demonstrates, remote sensing is without a doubt one of the indispensable tools for detecting changes in multiple facets of biodiversity over time.

Through this document, a number of applied researchers share their expertise in the use of remote sensing for monitoring indicators relevant to biodiversity. Using examples and simplified technical language they explain what is currently feasible with remote sensing and approximately at what cost. In this way, the document promotes a common understanding among technical specialists in remote sensing, environmental managers and policy makers and helps us make decisions on where, when and how to use remote sensing information. The collective experience represented here will help readers to identify feasible options for implementing activities that will monitor progress toward global, regional, and national goals and targets.

We hope the document will facilitate the widespread but judicious adoption of remote sensing in creating operational indicators for use by national agencies and also contribute to an improvement in the quality of global indicators. Remote sensing is not the only answer to monitoring the crisis of biodiversity loss, but strategic use of remote sensing data can greatly improve national, international, and organizational efforts to monitor progress toward the 2010 target.

Ahmed Djoghlaf,
Executive Secretary,
Convention on Biological Diversity

Jon Hutton,
Director, UNEP World Conservation Monitoring Centre

Teresa Fryberger,
Program Director, Applied Science Program, Earth Science Division, NASA

Contents

Chapter 1. Introduction

1.1 Purpose

The methods, cost and benefits of traditional biodiversity indicators (for example, species counts or total hectares in protected areas) are relatively familiar to environmental decision makers. In contrast, the complexity associated with the various integral components of remote sensing (radiative transfer, satellite technology, image processing, and field ecology among others) can be intimidating to nonspecialists and may preclude the adoption of truly useful applications. In other instances, many of those who have crossed the technological divide and seen map products and statistics resulting from remote sensing analysis may be overconfident about its potential to produce accurate environmental classifications and detect characteristics of ecosystem change. In reality, while remote sensing may represent the best way to measure characteristics of change over large areas, the accuracy of a given remotely sensed product may not be high enough for certain applications and for particular users.

There are several things environmental managers need to know for a practical understanding. For instance:

- What exactly does the information from a particular satellite sensor represent?
- How can this information be translated into a useful indicator?
- What are the common indicators associated with each major biome?
- What range of accuracy might one expect from a particular remotely sensed indicator, and what conditions affect this accuracy?

We address these and other questions while presenting the overall role that remote sensing can play for developing and monitoring biodiversity indicators relevant to various strategic components of the Convention on Biological Diversity (CBD). We touch on the relationships between measures made at the global level and at scales typical in national and local monitoring. We present examples of remotely sensed indicators for monitoring at the national and subnational levels. And lastly, we highlight practical tools, datasets and other resources readily accessible to remote sensing users.

The indicators covered in this book are based on the list identified for immediate testing and for further development by the CBD COP8 (Decision VIII/15). We concentrate on indicators that are relevant to both international and national decision makers and for which remote sensing is a highly relevant tool. We find that remote sensing data can make a strong contribution to six of the areas of interest identified by the CBD: (1) trends in extent of selected biomes, ecosystems and habitats; (2) coverage of protected areas; (3) threats to biodiversity; (4) connectivity or fragmentation of ecosystems: (5) trends in populations of selected species; and (6) potential human development indicators. Throughout the text, we present case studies that provide a rationale and resources for commonly used indicators within the context of real projects.

1.2 Audience

Because our intent is to bridge the gaps between technical specialists, on the one hand, and biodiversity managers, environmental managers, and policy makers, on the other, both should be considered the intended audience for this publication. However, the technical level and content is directed mainly at the latter group. For those with little background in the subject of remote sensing, we include a quick overview of the basics before addressing the various indicators remote sensing could help produce.

The information presented here is relevant for those involved in environmental monitoring including site-based monitoring and for those involved in governmental and intergovernmental processes. The

2010 Biodiversity Target is simultaneously a global and a national commitment that encourages countries to set national targets relevant to the 2010 assessment framework (if they have not done so already). The incorporation of 2010 Biodiversity Target and selected indicators into the Millennium Development Goals demonstrates the relevance of biodiversity and environmental monitoring for sustainable development.

1.3 Intended use

This sourcebook is intended to assist environmental managers and others who work with indicators in pursuing appropriate methods for indicator testing and production, and to offer some guidance to those responsible for the interpretation of indicators and implementation of decisions based on them. Upon reading this document, technical advisers, environmental policy makers, and remote sensing lab directors and project managers should be able to identify specific, relevant uses of remote sensing data for biodiversity monitoring and indicator development related to the CBD. It is also hoped that the sourcebook will assist in the planning and implementation of biodiversity-relevant indicators within other multilateral environmental agreements, including the Ramsar Convention on Wetlands and the United Nations Convention to Combat Desertification.

The appendices provide a greater level of detail for the environmental manager or analyst, indicating potential techniques for producing individual indicators using remote sensing, discussing technical issues, and listing available resources. However, this book is *not* intended as a substitute for one of the many excellent remote sensing and analysis manuals already available. Some recommended sources for further study are included in the appendices.

1.4 Organization

Chapter 2 gives the reader a general idea of the correspondence between biodiversity indicators and strengths of remote sensing technology. This chapter also outlines some of the inherent limitations of remote sensing that should be kept in mind when constructing indicators. It addresses the relevance of remote sensing measures to various CBD concepts, such as 2010 focal areas and Programmes of Work. We report on practical experience with remote sensing within the Biodiversity Indicators for National Use project which focused on the creation of practical national level indicators.

Chapter 3 offers a brief introduction to remote sensing methods and terminology. It strives to answer common questions about what remote sensing is and how it is used, and discusses general issues for the use of remote sensing within a biodiversity-monitoring framework.

Chapters 4 through 11 describe indicators identified and adopted for monitoring of progress toward the 2010 target. This section is the heart of the document, where the authors discuss a practical role for remote sensing in the development of indicators within the framework of the CBD's focal areas. For each focal area, we describe specific remote sensing weaknesses and strengths, identify suitable data sets and outline approaches for common indicators. These chapters also contain a number of case studies illustrating methods and data products in more detail. Not all the case studies involve national-scale results, but each illustrates indicator scenarios that may be of interest when planning national assessments and monitoring systems.

The appendices contain a glossary, listing of abbreviations and acronyms, links to and descriptions of large repositories of data, training resources and remote sensing tools on the web and elsewhere. Members of the NASA-NGO Working Group and UNEP-WCMC have pooled their collective knowledge and experience to list resources that might be useful for those engaged in biodiversity monitoring.

Chapter 2. Remote Sensing and monitoring for the Convention on Biological Diversity

AUTHORS: Holly Strand[1], Eugene Fosnight[2], Peter Herkenrath[3], Robert Höft[4]
CONTRIBUTORS: Woody Turner[5] Valerie Kapos[3], Eric Sanderson[6]

1 World Wildlife Fund (WWF-US) and Utah State University, 2 UNEP/GRID-Sioux Falls, 3 UNEP World Conservation Monitoring Centre, 4 Secretariat of the Convention on Biological Diversity, 5 NASA Headquarters, 6 Wildlife Conservation Society

2.1 The 2010 biodiversity target framework: Focal areas, goals, and subtargets

The 2010 biodiversity target is the keystone of the Strategic Plan of the Convention on Biological Diversity (CBD) adopted in 2002. The target is associated with seven focal areas designed to enhance the evaluation of progress in implementation. These focal areas represent the broad remit of the Convention, including not only issues of conservation and sustainable use of biodiversity, but also social considerations dependent upon the maintenance and use of biodiversity. Within each focal area, a provisional set of goals and subtargets helps clarify and assess progress toward the target, as well as promote coherence among the Programmes of Work of the Convention. Beyond its global application, this structure forms a flexible framework within which national or regional subtargets or both may be developed, according to priorities and capacities at these scales and taking into account differences in diversity between countries.

Table 2.1 highlights those areas within the CBD's current indicator framework (Decision VIII/15) where remote sensing can make an important contribution to indicators associated with set goals and targets. Within this particular framework, remote sensing has wider application at the national or sub-national level than at the global level. Furthermore, there are several global remote sensing measures outside this framework that can be used to discern trends in environmental conditions associated with biodiversity. Phenomena such as surface air and water temperatures, glacial retreat, energy use, and others can be measured successfully via satellite (for practical examples, see UNEP's Atlas of Our Changing Environment (2005)).

TABLE 2.1 Provisional Indicators for Assessing Progress towards the 2010 Biodiversity Target. Source: CBD Decision VIII/15. Indicators considered ready for immediate testing and use (green), and indicators confirmed as requiring more work (red). Indicators where remote sensing can make on important contribution are shown by a star.

Focal Area	Headline Indicators
Status and trends of the components of biological diversity	★ Trends in extent of selected biomes, ecosystems, and habitats ★ Trends in abundance and distribution of selected species ■ Coverage of protected areas ★ Change in status of threatened species ■ Trends in genetic diversity of domesticated animals, cultivated plants, and fish species of major socioeconomic importance
Sustainable use	■ Area of forest, agricultural and aquaculture ecosystems under sustainable management ■ Proportion of products derived from sustainable sources ★ Ecological footprint and related concepts

Focal Area	Headline Indicators
Threats to biodiversity	Nitrogen deposition ★ Trends in invasive alien species
Ecosystem integrity and ecosystem goods and services	■ Marine Trophic Index ★ Water quality of freshwater ecosystems ■ Trophic integrity of other ecosystems ★ Connectivity / fragmentation of ecosystems ■ Incidence of human-induced ecosystem failure ■ Health and well-being of communities who depend directly on local ecosystem goods and services ■ Biodiversity for food and medicine
Status of traditional knowledge, innovations and Practices	■ Status and trends of linguistic diversity and numbers of speakers of indigenous languages ■ Other indicator of the status of indigenous and traditional knowledge
Status of access and benefit-sharing	■ Indicator of access and benefit-sharing
Status of resource transfers	■ Official development assistance provided in support of the Convention ■ Indicator of technology transfer

2.2 What is an indicator?

An indicator can be defined as a measure used to determine the performance of functions, processes, and outcomes over time. Within the context of the CBD, these measures are useful only if they address questions relevant to actual activities or priorities of the Strategic Plan, various programmes of work, or national biodiversity strategies. Furthermore, indicators are feasible only if the data to generate them can be realistically obtained. SBSTTA guidelines on designing national-level monitoring and indicators (CBD 2003) offer much practical guidance on the process of indicator development according to the process shown in figure 2.1. They state that indicators should be problem oriented (focusing on human-caused change, not natural fluctuations), simple to understand, and inexpensive enough to be implemented over the long term. The indicators listed by the CBD for testing at a global scale are very broad (for example, "connectivity/fragmentation of ecosystems"), leaving room for different methods of measurement and interpretation. In contrast, indicators used at a national scale should be defined and explained precisely in relation to the key question(s) and policies they are intended to address.

Remotely sensed images do not represent biodiversity indicators per se. Rather, remote sensing data form the raw inputs from which indicators can be constructed. For example, the signal to remote sensors can be associated with a particular vegetation cover type (such as forests). A change in the signal from one time period to another might indicate a change in vegetation cover and the habitat that is associated with that cover. Validation with ground truth or by high resolution data is necessary to confirm remote sensing observations. Data manipulation within a GIS environment can help produce the maps and statistics needed to create an indicator that can be understood by decision makers and the general public.

Indicators can be simple, based on single variables, or composite indicators, based on a combination of multiple variables, with the benefits of simplicity versus comprehensiveness. An example of a simple indicator for biodiversity created from remote sensing data might be "area of *x* land cover (as a surrogate

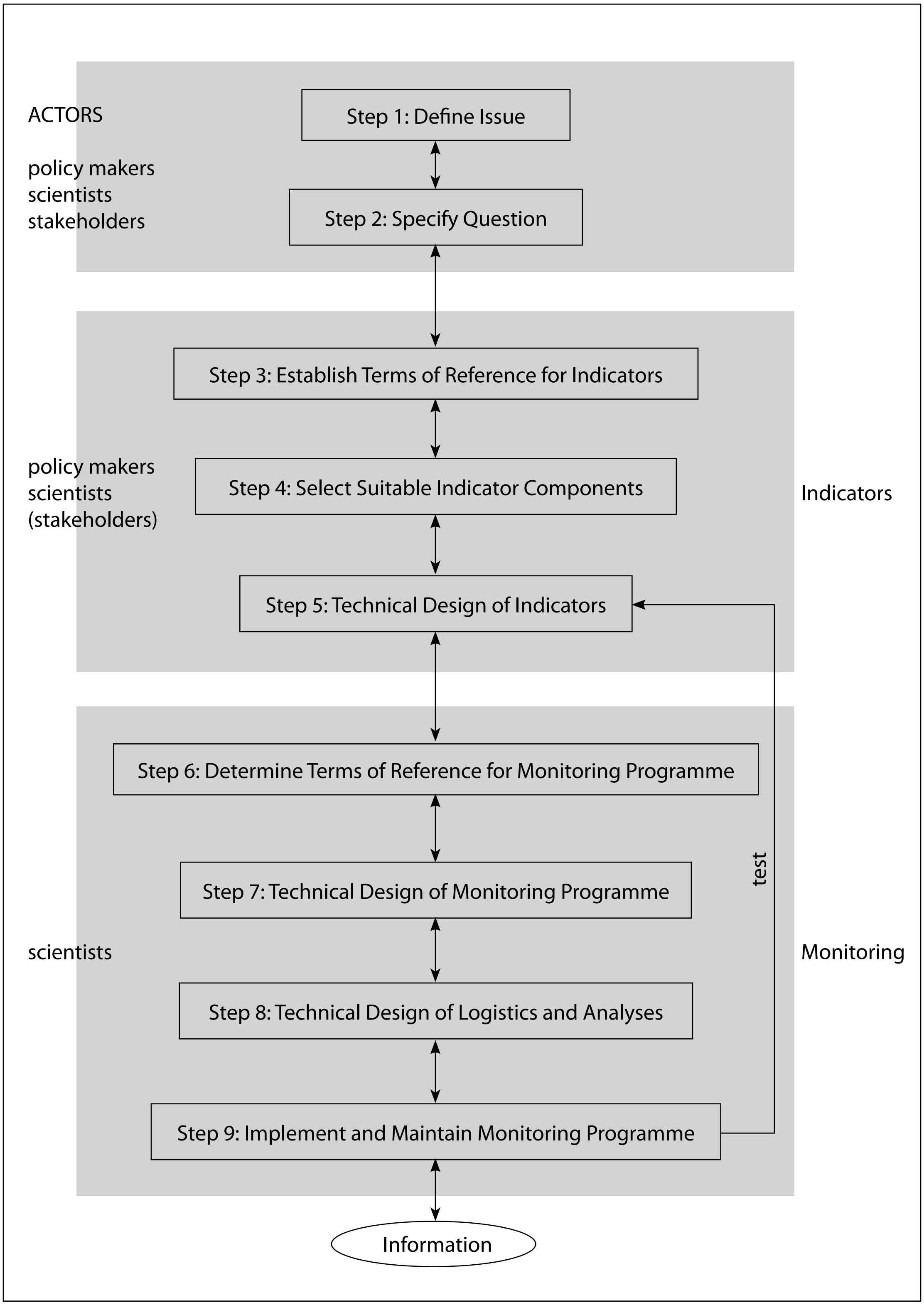


FIGURE 2.1 Steps in indicator selection and design. Source: CBD 2003a and CBD 2003b.

for habitat) over time." In contrast, a complex indicator is composed of multiple variables and is often represented by an index. Good examples of complex indicators for biodiversity at the global scale are contained within Sanderson et al. *State of the Wild* (2002).[1] This assessment demonstrated how to combine global data sets on human population density, land transformation (derived from remote sensing), accessibility (distance from major roads, rivers, and coastlines), and electrical power infrastructure to create an index of human influence on land and to map relative wildness (or intactness) at one-kilometre resolution. (See figure 2.2A and B). In addition, the same data were used to identify "wildland seeds" or relatively small areas with low human impact that might be considered important regional nodes of conservation and restoration (not shown).

Wackernagel also created a resource accounting system that tracks human demand on nature, called the Ecological Footprint. Results are published in a number of publications and websites, including WWF's biennial *Living Planet Report* (WWF, Global Footprint Network, Zoological Society of London, 2006). The Footprint is composed of two parts: national Footprint (human demand on nature) and national biocapacity (availability of nature). The system uses as inputs a number of data points that were generated through remote sensing. For example, it uses information from the Global Agro-Ecological Zones (International Institute for Applied Systems Analysis [IIASA] and Food and Agriculture Organization [FAO] 2000), which in turn relies on GIS layers of 12 land cover classes produced by remote sensing as one of its primary inputs. The relative productivity of cropland, pasture, forest, and built-up areas is calculated using these data points.

Remote sensing information and resulting indicators may be presented as maps, graphs, or tables, depending on the type of data available, the importance of the spatial pattern of the indicator, and the ease of interpretation to the target audience. Mapped indicators have strong visual impact, and the geographic frame of reference provides context and highlights links that might otherwise not be obvious to many potential users.

2.3 The 2010 target and formation of indicators

Most indicators represent a defined measurable attribute or condition. Within a monitoring framework they are produced and compared at successive points in time. However, the 2010 biodiversity target specifies a decrease in terms of the *rate* of biodiversity loss. Therefore, indicator values need to be further translated into rates if they are to measure progress toward the 2010 target. Figure 2.3 illustrates this point, using area of forest values from the FAO (2005) as an example data set. This data set includes the area of both natural and plantation forests, as assessed by the FAO on the basis of national statistics. If this measure were selected as an indicator of trends in extent of ecosystems, the 2010 target would be to slow the rate of decline in forest area.

Figure 2.3A shows that of the five FAO regions with the greatest forest area in 1990, forest area decreased for both periods measured (1990–2000 and 2000–05) in South America, South and Southeast Asia, and West and Central Africa. Figure 2.3B presents the same data in a form relevant to the target. In the latter figure, a positive slope indicates success in the terms of the target—a decrease in the rate of loss. The data suggest that for the 2000–05 period compared to the 1990–2000 period, there was a decrease in the rate of loss for West and Central Africa, while the rate of loss for both South America and South and Southeast Asia increased. The rate of change for both Europe (including the Russian Federation) and North America was stable, with Europe having a small, steady percentage increase in forest area; there was no change in North America. Thus, three points are required to obtain the minimum two rates of change needed to confirm or deny a reduction in the rate of biodiversity loss.

1 Sanderson et al. produced complex indicators for a one-time assessment rather than indicators as part of an operational monitoring system.

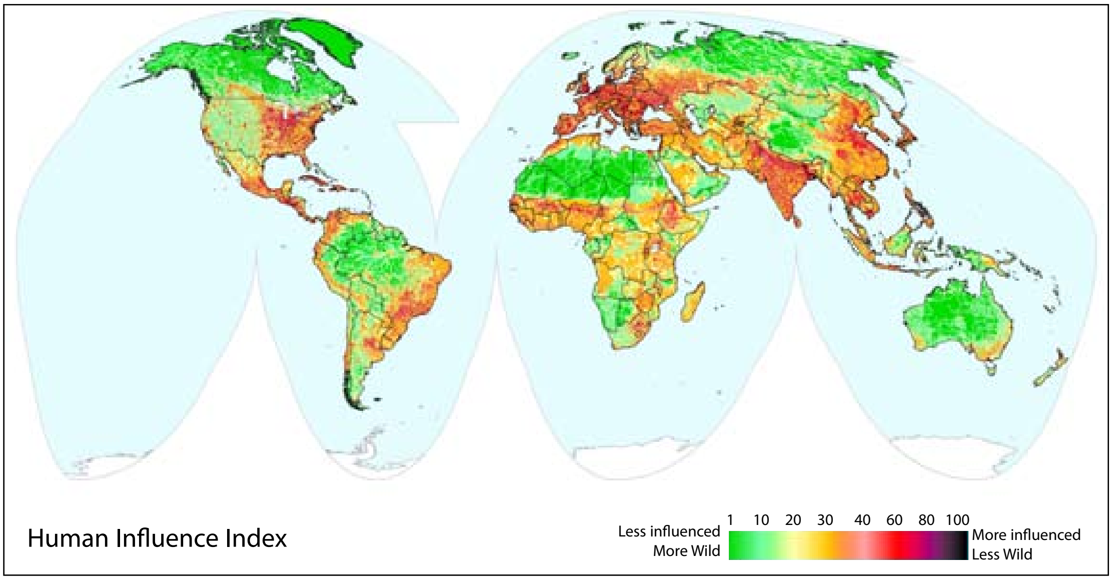


FIGURE 2.2A The human footprint shown as normalized Human Influence Index (HII). The higher the score, the higher is the concentration of human use. Source: Wildlife Conservation Society and CIESIN.

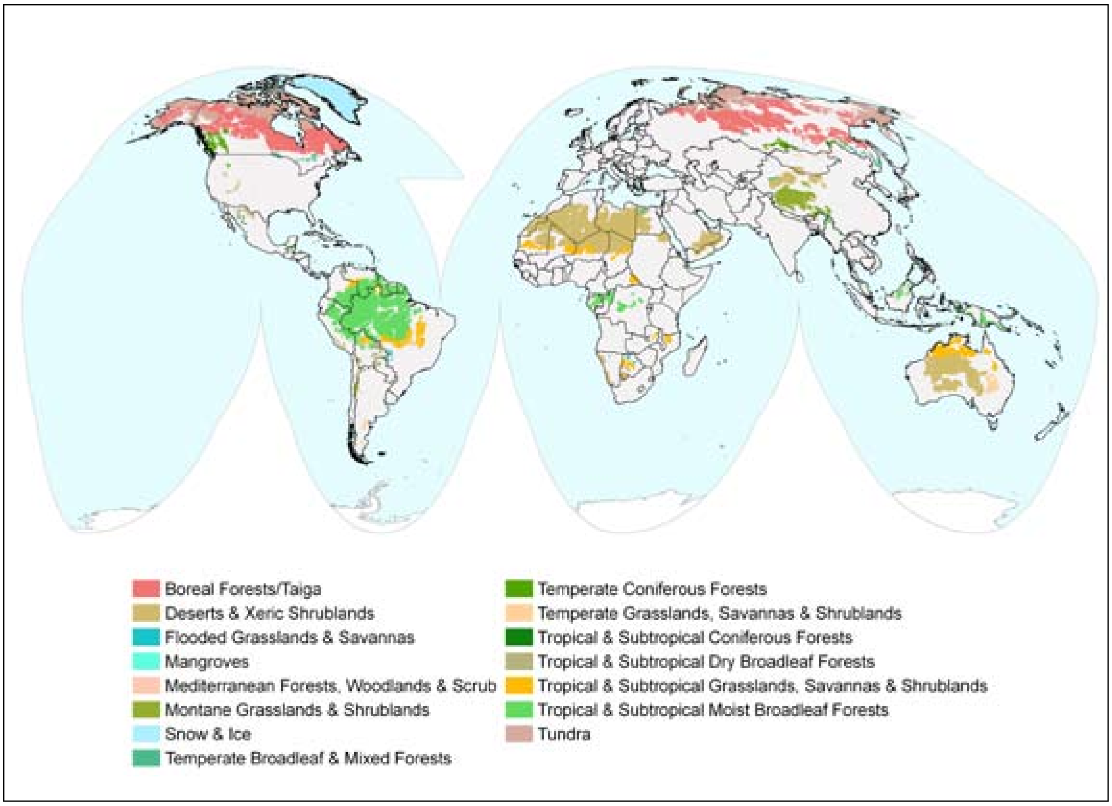


FIGURE 2.2B In contrast, Last of the Wild areas experience relatively low HII scores. These areas represent the best examples of remaining wilderness within each of the world's biomes. Source: Wildlife Conservation Society and CIESIN.

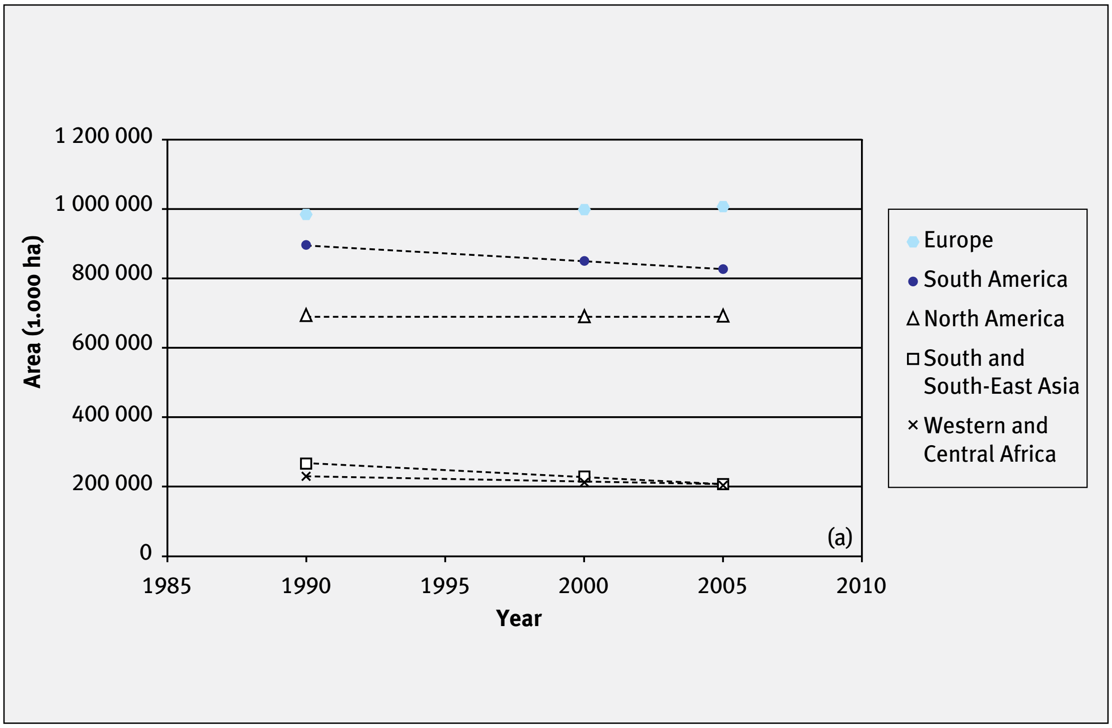


FIGURE 2.3A. Area of forest through time by FAO region. Source F AO (2005)

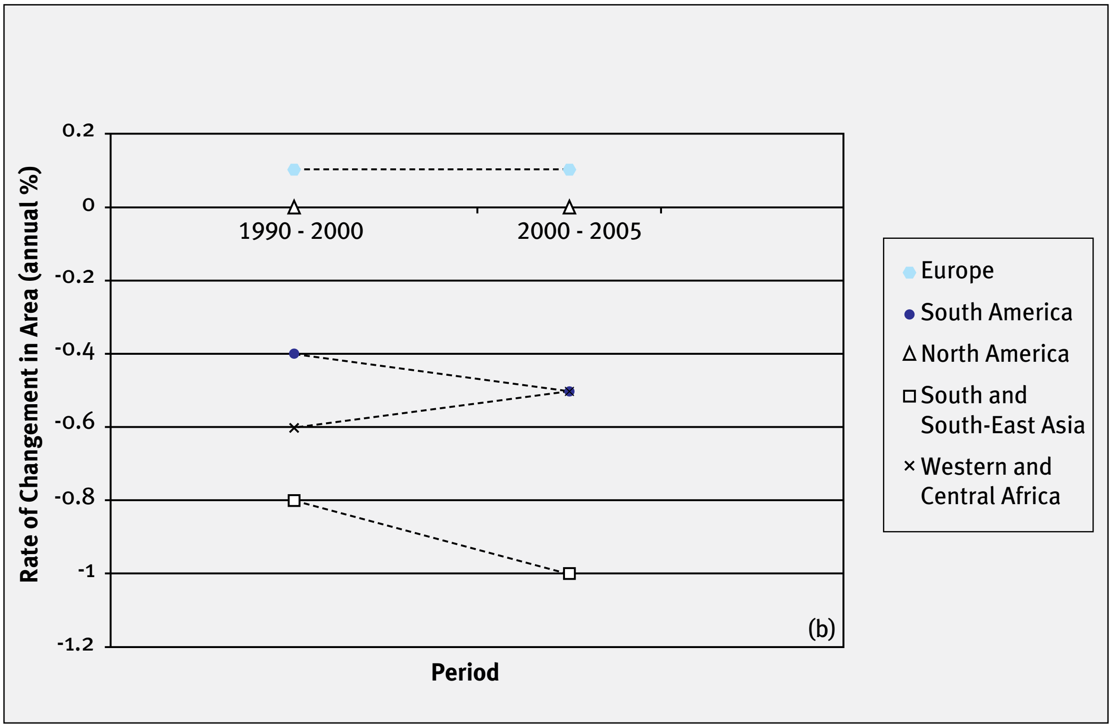


FIGURE 2.3B. Rate of change of forest area through time by FAO region. Source: FAO (2005).

The reality is that few countries have data attained by a consistent method for three dates in a row. However, many countries do have high-quality land cover maps derived from satellite data. Often, these are overlaid with maps of protected area boundaries to determine the degree of protection of different ecosystem types and states (see the example in figure 2.4). Although one or two photographs of land cover cannot yet be considered an indicator of progress toward the 2010 goal, these data may serve as baseline data for monitoring in the future.

2.4 Use of biodiversity indicators in national assessments

The framework and indicators selected by the CBD to assess global progress toward the 2010 biodiversity target provide a starting point for developing indicators for national use. As countries track their own progress toward 2010 and beyond, they may have alternative or additional needs for indicators. These needs are dictated by national and subregional policy priorities, which may differ from the global priorities. Therefore, our discussion of remote sensing indicators will go somewhat beyond those in the current global framework and will touch on a variety of remote sensing measures within each focal area.

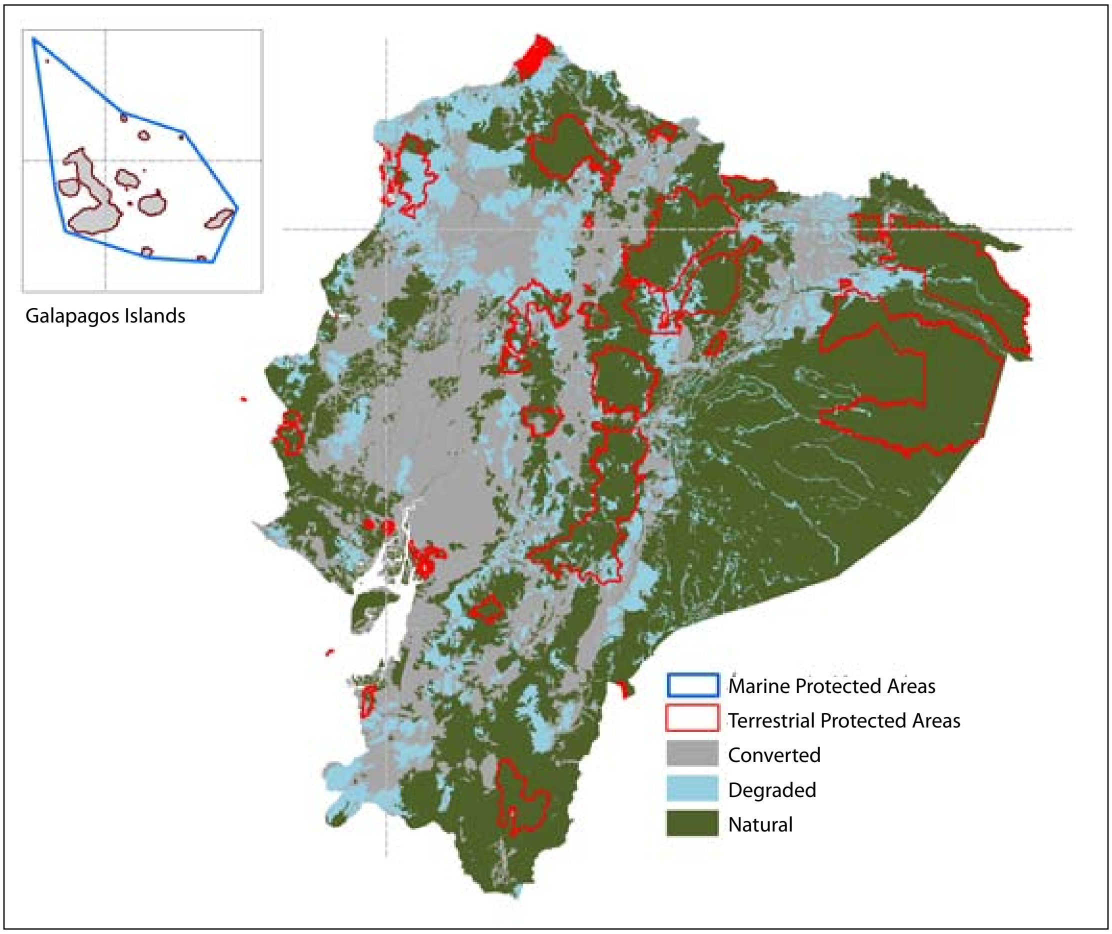


FIGURE 2.4 Protected areas (numbered) in continental Ecuador in relation to areas of largely natural, disturbed, and converted vegetation. Source: Ministerio del Ambiente del Ecuador and Fundación EcoCiencia (2005)

In the recent Global Environment Facility–funded project, Biodiversity Indicators for National Use (BINU), Bubb et al. (2005) identified useful applications of remotely sensed data in generating biodiversity indicators to address key questions raised at the national scale. In each of the four countries involved in this project, (Ecuador, Kenya, the Philippines, and Ukraine), at least one of the key questions concerned changes in land cover and land use and its effects on biodiversity.

One important lesson in all the BINU countries was that although the maps were often useful, they are not always easy for decision makers to interpret, and the conclusions drawn from them as indicators were sometimes ambiguous. Graphical summaries of statistical data drawn from maps can be more useful tools than the maps themselves in some instances. Graphs may especially be less cumbersome in presenting time courses of change in multiple variables. Figure 2.5 shows an example from the Philippines in which long-term data on national mangrove cover, some of which are derived from remote sensing, are plotted alongside data on human population and aquaculture development, two measures of pressure on mangrove ecosystems.

All of the countries involved in BINU found data from remote sensing to be useful in developing biodiversity indicators for national use. However, all countries identified the costs associated with routine updating of satellite-based data to be a major challenge. Another complication for some countries is that many existing map products are derived from imagery obtained by different sensors at different resolutions and often from multiple or unspecified dates or both, thus introducing an unknown amount of error into the results.

Countries participating in BINU found that the capacity to use spatial data to identify, analyse, and interpret decision makers' key questions was not always available. In addition, collaboration among

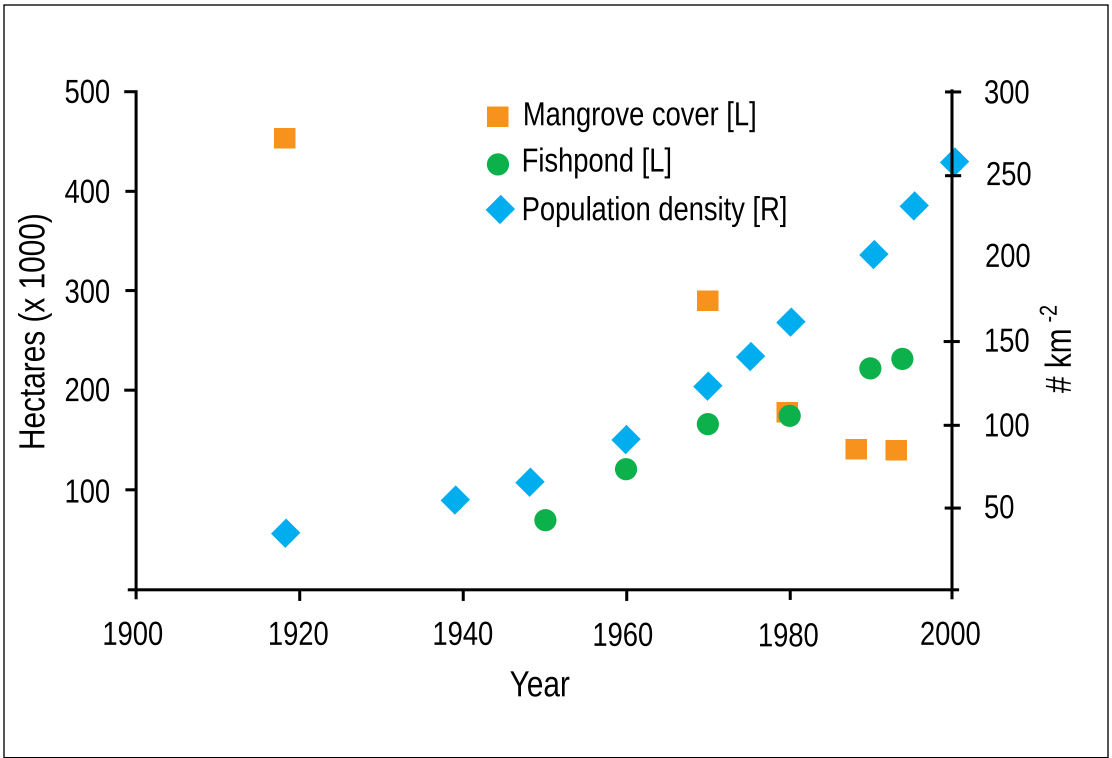


FIGURE 2.5 Relationship between mangrove cover (in ha), fishpond area (in ha), and population density (# km²) in the Philippines. Source: Bureau of Fisheries and Aquatic Resources and the Protected Areas and Wildlife Bureau, the Philippines cited in Bubb et al. (2005).

individuals and groups with a diverse range of skills was vital to ensure that key questions were being adequately addressed and that indicators were being properly assessed and communicated clearly to the target audience. Maps do not act as indicators in and of themselves. Users, therefore, may require assistance in making clear the most important insights made. Sometimes, combining maps with statistical tables and graphs is helpful in accomplishing this goal.

In summary, it is clear from the experience of the BINU project that remote sensing can play an important role in generating biodiversity indicators for national use, but care must be taken to identify the key questions for which indicators are needed and communicate effectively with the decision makers who are expected to use them.

2.5 National-global monitoring linkages

The CBD framework for assessing progress toward the 2010 biodiversity target includes global headline indicators. Ideally, processes at the global, regional, national and local levels would use the same indicators. Such an approach would allow building global biodiversity monitoring information from local, national and regional data. The adoption by the Council of Europe of the CBD indicators into the process Streamlining European Biodiversity Indicators (SEBI2010) is an example of the synergy that can be produced by aligning indicators. The initiative is finalizing its indicators in 2007, which will be informed by national statistics offices and represent an example of a bottom-up approach to biodiversity monitoring.

However, a perfectly aligned, nested system of parallel indicators is not possible or perhaps even desirable at this time. Specific monitoring needs vary from country to country, many monitoring systems were created before the 2010 framework was designed, and methods for even the same indicators vary from place to place. Therefore, it is not possible to upscale national biodiversity information for global indicators. The only realistic approach is that countries and regional efforts are free to identify and develop their own indicators with regard to their own interests and capacity.

Pereira and Cooper (2006) therefore propose a dual scale approach to the global monitoring of biodiversity with global- and regional-scale programmes at the species and ecosystem levels. The global-scale programmes would follow a top-down approach, with an emphasis on central coordination, consistency and transparency, whereas the regional-scale programmes would follow a bottom-up approach, with an emphasis on regional management needs and capabilities.

The global scale monitoring of ecosystems would entail the production of consistent global land-cover maps based on remote sensing; as well as a global network for monitoring habitats that are best monitored, or have particular relevance, at the regional level (e.g., wetlands, coral reefs). The second edition of Global Biodiversity Outlook (www.cbd.int/gbo2) reports on existing global maps on trends in the extent of selected ecosystems and their integrity.

A dual approach is also planned for FAO's 2010 Global Forest Resources Assessment. In addition to data provided by countries on the basis of national forest inventories, remote sensing would provide complementary information on the spatial distribution of forests and on forest and land cover and land-use change dynamics at the biome, regional and global level. In most instances, cross-referencing remote sensing data with field assessments can improve the quality and between-year standardization for national assessments also. More often than not, national ecosystem assessments are produced from field estimates. However, by marrying field data with the technological capabilities of remote sensing more area can be covered and more frequently. Given some level of coordination and classification harmonization, ground information and remote sensing results from national assessments would ideally be used to calibrate and validate global models thereby greatly improving our ability to monitor the global state of biodiversity.

Currently, there are a few global land-cover data sets that contribute to our knowledge of the distribution of ecosystems, and all but one are produced by remote sensing (see table 2.2). However, none of the

TABLE 2.2: Global land cover maps available on the Internet

Data set name	URL	Spatial resolution	Sensor used	Year
Global Land Cover-2000	http://www-gvm.jrc.it/glc2000/	1 Km	SPOT Vegetation	2000
MODIS Land Cover	http://lpdaac.usgs.gov/ modis/mod12q1v4.asp	1Km	MODIS	Yearly starting in 2001
FAO Global Forest Resources Assessment	www.fao.org/forestry/site/global-fra/en	N/A – Statistics only, no mapped output	Varied – compiled from country reports	2005
AVHRR Global Land Cover	http://glcf.umiacs.umd.edu/data/landcover/	1 Km, 8 Km, 1 degree	AVHRR	1993
IGBP DISCover	http://edcsns17.cr.usgs.gov/glcc/	1 Km	AVHRR	1993

global datasets are directly comparable with each other as they all come from different satellite systems and/or use different classification systems. The SPOT and MODIS products (Bartholomé et al. 2005 and Friedl et al. 2002 respectively) are most promising as they are constructed of finer resolution data that will detect changes in smaller areas. The GLOBCOVER project, an initiative of the European Space Agency (http://www.esa.int/esaEO/SEMGSY2IU7E_index_0.html), includes the production of global land-cover maps for the years 2005 and 2010 using a classification system compatible with the GLC 2000. However, it will be based on data from a different sensor (ENVISAT-MERIS) and at a different resolution from GLC 2000. Only through validation can we determine the reliability of change detection between these two datasets.

In an attempt to relate different land cover hierarchies and classifications — such as exist now in many national and global systems — FAO developed the Land Cover Classification System (LCCS) (Di Gregorio and Jansen 2000), which has since been further refined (FAO 2005 http://www.fao.org/docrep/008/y7220e/y7220e00.htm#Contents). The LCCS represents a comprehensive, standardized *a priori* classification system, created for land cover mapping and independent of the scale or mapping method. The classification uses a set of independent diagnostic criteria that allow correlation with existing classifications and legends. The system could therefore serve as a reference base for land cover. The methodology is comprehensive in the sense that any land cover identified anywhere in the world can be readily accommodated. Because of the heterogeneity of land cover, the same set of classifiers cannot be used to define all land cover types. The hierarchical structure of the classifiers may differ from one land cover type to another. Therefore, the LCCS has two main phases: 1) an initial *Dichotomous Phase*, where eight major land cover types are distinguished; and 2) a subsequent *Modular-Hierarchical Phase* where the set of classifiers and their hierarchical arrangement are tailored to the major land cover type. This approach allows the use of the most appropriate classifiers and reduces the total number of impractical combinations of classifiers. Because of the complexity of the classification and the need for standardization, a software application has been developed to assist the interpretation process. This will reduce inconsistencies between interpreters and between interpretations over time.

2.6 CBD and remote sensing needs

2.6.1 Coordination of scientific and conservation monitoring communities

The recent agreement at the Third Earth Observations Summit to establish a Global Earth Observation System of Systems (GEOSS, http://www.earthobservations.org/progress/geoss_progress.html) could facilitate and contribute to the monitoring scenario described above. GEOSS will focus on nine societal benefit areas, two of which address biodiversity and ecosystems management and protection. Thus, through GEOSS, there is an open window of opportunity for the scientific and conservation communities to tackle some of the challenges associated with biodiversity monitoring, e.g.: the comparability of existent land-cover data sets, the development of classification systems differentiating natural forest from industrial tree plantations, and assembling useful global remote-sensing data sets for dryland degradation.

2.6.2 Higher accuracy of measurements and classifications

The accuracy of global land cover datasets and global land cover change datasets needs to improve. The collection and distribution of land cover and land cover change validation (ground truthing) data is necessary to guide the classification process and assess the accuracy of the final product. Unfortunately, there remains a lack of international coordination and standardization in this component (Strahler et al. 2006; Wulder et al. 2006). There are several independent efforts collecting and cataloging these data but they are typically not shared. Reasons for not broadly distributing these data include:

- Validation data are typically collected for a specific project and are not in a format that is suitable for easy query and use by others.
- Some projects have no interest in sharing their data possibly to maintain a competitive edge over other researchers.
- There are no widely accepted standards for the collection, archiving, and distribution of validation data.

This is an area where the conservation community, with their broadly distributed network of project sites, can have a significant impact to support land cover mapping and monitoring. One effort that is trying to accomplish this task is the Global Integrated Trends Analysis Network (GITAN http://rockyitr.cr.usgs.gov/gitan/) which is a network of collaborators interested in understanding the types, causes, and consequences of change on the landscape. A component of GITAN is the System for Terrestrial Ecosystem Parameterization (STEP) database. STEP stores land surface parameters and was designed as a tool for training and validating land cover maps. Two other global scale validation efforts include:

- CEOS working group on calibration and validation: http://lpvs.gsfc.nasa.gov/
- MODIS land validation: http://landval.gsfc.nasa.gov/index.php

2.6.3 Continuity of data sources

Continuous long term satellite data from a single platform are needed to achieve the highest levels of accuracy for detecting change. Currently, the longest continuous stream of data comes from the Landsat series of satellites, which has been operational since 1972. The three most popular long-running optical satellite programmes, Landsat, SPOT, and IRS are expected to continue well into the future although there will likely be a significant gap in the Landsat acquisitions due to problems with Landsat 7 and delays developing a successor. The continuation of these and other missions into the future is critical for the national and regional monitoring programmes that rely on their data products.

2.6.4 Periodic data buys to release to all those who could not otherwise afford to buy the imagery

Periodic data buys of global wall-to-wall distributions make data economically accessible to developing countries. An example is the Global GeoCover-Ortho database which resulted from a 1998 contract between NASA and Earth Satellite Corporation (EarthSat) as part of the NASA Scientific Data Buy program. The majority of the data was acquired by the Landsat Thematic Mapper (TM) and Multispectral Scanner (MSS) remote-sensing systems; consequently, the GeoCover-Ortho images are the most accurate freely available satellite-derived base maps of the world. With a positional root mean square error of less than 50 m, they are more accurate than most of the world's 1:200,000-scale maps. Furthermore, owing to the nature of the original contract set up by NASA, this imagery is more economically accessible for developing countries. It is a comprehensive global data set with image dates ranging from 1970's to 2002 and is suited to establishing a worldwide environmental baseline. Additional Landsat TM images (and many other types of remotely sensed data) can be overlaid on the GeoCover-Ortho imagery for purposes of change detection. Subsequently, Landsat Orthorectified Pansharpened ETM+ data were compiled through NASA's Commercial Remote Sensing Program producing a 15m data set that is available from EarthSat Corp. for a nominal cost. For more information, see http://edc.usgs.gov/products/satellite/earthsattm.html or http://glcf.umiacs.umd.edu/portal/geocover/.

2.6.5 Technology transfer

Many countries lack the technology and trained personnel to take advantage of remote sensing for operational monitoring. Technology transfer is needed from those that do, as well as from non-governmental organizations with experience in biodiversity monitoring.

2.6.6 Datasets designed to support the reporting requirements of various environmental treaties and agreements

Datasets should be designed to fit the criteria for more than one environmental agreement when possible. There is an ongoing effort to coordinate CBD reporting requirements with other environmental treaties and multinational environmental agreements such as the Kyoto Protocol, UN Convention to Combat Desertification, Ramsar Convention on Wetlands, and Montreal Process. De Sherbinin (2005) outlines the information needs of these treaties discusses the feasibility of remote sensing for monitoring and assessment as well as other support functions including issue definition, implementation review, compliance, dispute resolution and public education. Remote Sensing in Support of Ecosystem Management Treaties and Transboundary Conservation.

2.7 References

Bartholomé E and A. Belward. 2005. GLC2000: A new approach to global land cover mapping from Earth. *International Journal of Remote Sensing* 26(9), 1959-1977.

Bubb, P., M. Jenkins, and V. Kapos. 2005. Biodiversity Indicators for National Use: experience and guidance. Cambridge. UNEP-WCMC. http://www.unep-wcmc.org/collaborations/BINU. (accessed January 20, 2006).

CBD. 2003a. Monitoring and Indicators: Designing National-Level Monitoring Programmes and Indicators. Ninth meeting. Montreal, November 10–14. Item 5.3 of the provisional agenda. Subsidiary Body on Scientific, Technical and Technological Advice, Secretariat of the Convention on Biological Diversity, Montreal, Québec, Canada. UNEP/CBD/SBSTTA/9/10. http://www.cbd.int/doc/meetings/sbstta/sbstta-09/official/sbstta-09-10-en.pdf (accessed May 22, 2007).

CBD. 2003b. Report of the Expert meeting on indicators of biological diversity including indicators for rapid assessment of inland water ecosystems. Ninth meeting. Montreal, November 10–14. Item 5.3 of the provisional agenda. Subsidiary Body on Scientific, Technical and Technological Advice, Secretariat of the Convention on Biological Diversity, Montreal, Québec, Canada. UNEP/CBD/SBSTTA/9/INF/7. http://www.cbd.int/doc/meetings/sbstta/sbstta-09/information/sbstta-09-inf-07-en.doc (accessed May 22, 2007).

De Sherbinin, A. 2005. Remote Sensing in Support of Ecosystem Management Treaties and Transboundary Conservation. Palisades, NY: CIESIN at Columbia University. Available online at http://sedac.ciesin.columbia.edu/rs-treaties/laguna.html.

Di Gregorio, A., and L. M. J. Jansen. 2000. Land Cover Classification System (LCCS): Classification concepts and user manual. Environment and Natural Resources Service, GCP/RAF/287/ITA Africover–East Africa Project and Soil Resources, Management and Conservation Service, Rome. FAO.

EROS Data Center. 2000. Land cover characteristics database, Version 2.0. http://edcwww.cr.usgs.gov

FAO. 2005. *Forest Resources Assessment 2005*. Food and Agriculture Organization of the United Nations, Rome, Italy. http://www.fao.org/forestry/site/fra2005/en (accessed January 29, 2006).

Friedl, M.A., D. K. McIver, J. C. F. Hodges, X. Y. Zhang, D. Muchoney, A. H. Strahler, C. E. Woodcock, S. Gopal, A. Schneider, A. Cooper, A. Baccini, F. Gao, and C. Schaaf 2002: Global land cover mapping from MODIS: algorithms and early results, *Remote Sensing of Environment*, Vol. 83 (1-2), pp. 287-302.

Hansen, M.C., R.S. Defries, J.R.G. Townshend, and R. Sohlberg. 2000. Global land cover classification at 1 km spatial resolution using a classification tree approach. *International Journal of Remote Sensing* 21(6/7):1331–64.

IIASA and FAO. 2000. Global Agro-Ecological Zones (GAEZ) 2000 CD-ROM. International Institute for Applied Systems Analysis (IIASA) and Food and Agriculture Organization (FAO), Rome.

Loveland, T.R., B.C. Reed, J.F. Brown, D.O. Ohlen, Z. Zhu, L. Yang, and J.W. Merchant. 2000**.** Development of a global land cover characteristics database and IGBP DISCover from 1 km AVHRR data. *International Journal of Remote Sensing* 21(6/7): 1,303-1,330.

Pereira, H. M., and D. Cooper. 2006. Towards the global monitoring of biodiversity change. *Trends in Ecology and Evolution* 21.3:123–9.

Sanderson, E., J. Malanding, M. A. Levy, K. H. Redford, A. V. Wannebo, and G. Woolmer. 2002. The human footprint and the last of the wild. *Bioscience* 52(10):891–904. www.wcs.org/humanfootprint (accessed May 2007).

Secretariat of the Convention on Biological Diversity 2006. Global Biodiversity Outlook 2. Montreal

Strahler, A. H., L. Boschetti, G. M. Foody, M. A. Friedl, M. C. Hansen, M. Herold, P. Mayaux, J. T. Morisette, S. V. Stehman, and C. E. Woodcock1. 2006. Global land cover validation: recommendations for evaluation and accuracy assessment of global land cover maps, EUR 22156 EN. European Union.

UNEP. 2005. One Planet Many People: Atlas of Our Changing Environment. Division of Early Warning and Assessment (DEWA) United Nations Environment Programme UNEP. Nairobi, Kenya

Wulder, M. A., S. E. Franklin, J. C. White, J. Linke, and S. Magnussen. 2006. An accuracy assessment framework for large-area land cover classification products derived from medium-resolution satellite data. *International Journal of Remote Sensing* 27:663-683.

WWF, Zoological Society of London, Global Footprint Network. 2006. Living Planet Report. Gland, Switzerland, 40 pp. http://assets.panda.org/downloads/living_planet_report.pdf (accessed 13 June 2007)

Chapter 3. The Basics of Remote Sensing

AUTHORS: Marc Steininger[1], Ned Horning[2]
REVIEWERS: Eugene Fosnight[3], James Strittholt[4]

1 Conservation International, 2 Center for Biodiversity and Conservation of the American Museum of Natural History, 3 UNEP-Sioux Falls 4 Conservation Biology Institute

3.1 Background

Remote sensing is well recognized for the integral role it plays in environmental assessment and monitoring. Field surveys provide higher levels of accuracy than remote sensing, but using remote sensing techniques makes it possible to increase the speed and frequency with which one can analyse a landscape. Therefore, remote sensing can aid in making quick and focused decisions. Furthermore, remote sensing contributes to the development of objective and comprehensive assessments over larger geographic extents than is possible with fieldwork alone. Remote sensing facilitates objective, repeatable analyses that can help detect and monitor change over time, which is critical to the development of indicators for the 2010 target.

As a rule, remote sensing studies require additional (ancillary) data to allow the imagery to be interpreted. Ground sampling, familiarity with land cover and land use of the area in question, and expert knowledge of species trends and habitat usage, ecological communities, and ecological systems are needed to form a solid basis for interpretation. Although remote sensing provides repeated observation of the Earth's surface, it has limited spatial, temporal, and thematic resolution (defined later in this chapter). Field sampling provides detailed, local biological information for small areas, but it can be expensive. Used together, strategic ground sampling, expert knowledge, and interpretation of remote sensing imagery can form a reliable, repeatable, and cost-effective analytical framework for accurately assessing the rate of change in biological diversity.

There are two general approaches to using remote sensing in assessing biodiversity. One is direct remote sensing, which maps individual organisms, species assemblages, or ecological communities by use of airborne or satellite sensors. The other approach, indirect remote sensing, facilitates assessments of biodiversity elements through analysis of such environmental parameters as general land cover, geology, elevation, landform, human disturbance, and other surrogates for the actual features of interest. When mapping the distribution of species of interest (focal species), a common approach is to map specific habitat types by use of a combination of remote sensing and environmental data themes. For example, woodland caribou (*Rangifer tarandus*), a species at-risk in the boreal zone of North America, is dependent on old-growth forest isolated from human disturbance. Mapping and monitoring woodland caribou distribution can be achieved by relying on remote sensing to map the vegetation modified by spatially explicit data on human disturbance, including roads, agricultural development, forestry activities, and energy development. Combining spatial data sets is the most common means of assessing and tracking selected species. Additional examples are discussed in more detail in Chapter 4.

3.2 What exactly is remote sensing?

Any method of observing the Earth's surface without being directly in contact with it falls under the definition of remote sensing. These methods allow us to obtain information about our planet and human activities from a distance, which can reveal features, patterns, and relationships that may not be possible or affordable to assess from ground level. Remote sensing provides an overview of the interaction of our complex biosphere components and is especially useful in monitoring landscape change.

The most common tools used for remote sensing are airborne sensors installed on fixed-wing planes or helicopters, as well as on various satellite sensors orbiting the Earth. The airborne sensors are typically used to collect data on demand, when they are needed. Airborne data collection is most valuable for small areas, for specific events, to complement less detailed data, and for validation of data collected by satellite sensors over larger areas. Historical aerial photography archives can also be critical in change detection for periods before the widespread availability of satellite technology, which occurred in the mid-1970s.

Remote sensing satellite systems for land cover assessment are operated by a growing number of countries, including Brazil, Canada, China, France, India, Japan, Russia, and the United States. Many satellites monitor the earth, with different sensors gathering different types of environmental data. The sensors acquire images of the earth and transmit them to ground receiving stations located throughout the world. Once these raw images are processed and analysed, indicators of biodiversity change can be assessed.

3.3 Spectral images

Satellites view the planet with sensors that provide digital images of several discrete areas of the light spectrum. Human vision is limited to the visible wavelengths from blue to red, but satellite sensors are not so limited. Most satellite sensors also record images in wavelengths invisible to us, such as in the near-infrared and thermal regions (figure 3.1). Some can detect even longer wavelengths, such as in the microwave region. Images from these different wavelength areas or bands can be combined in different ways to produce false-colour images for human viewing, interpretation, and analysis (figure 3.2).

Because the images are collected in a digital format, they can be analysed by computer. Just as different objects reflect different visible wavelengths, resulting in the colours the human eye can see, objects also reflect other non-visible wavelengths in different ways that are also important in classification. For example, geologists can distinguish rock and mineral types from space by using images taken in the middle-infrared, although most rocks and minerals look fairly similar in the visible wavelengths.

The most commonly used data in land cover mapping are from optical sensors—instruments that detect short-wave solar energy reflected off the Earth's surface. These sensors analyse three main regions of the spectrum, the visible, near-infrared, and middle-infrared. Most remote sensing of land cover types is dependent on the fact that in these main regions, reflectance differs significantly for different surfaces such as soil, leaves, wood, ash, water, and snow (figure 3.3). In vegetation, the canopy structure affects

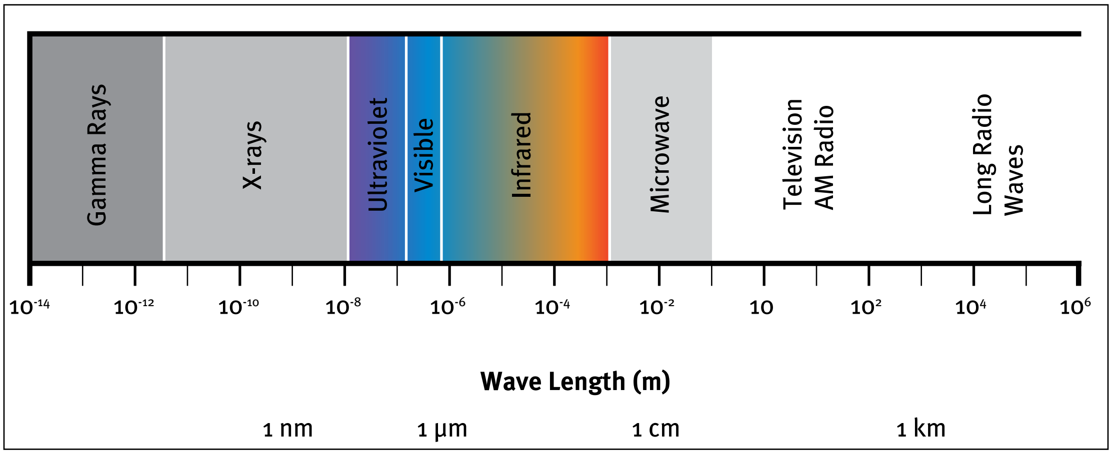


FIGURE 3.1 Spectral chart. Source: Short, N.M. NASA remote sensing tutorial http://rst.gsfc.nasa.gov (accessed April 12, 2007).

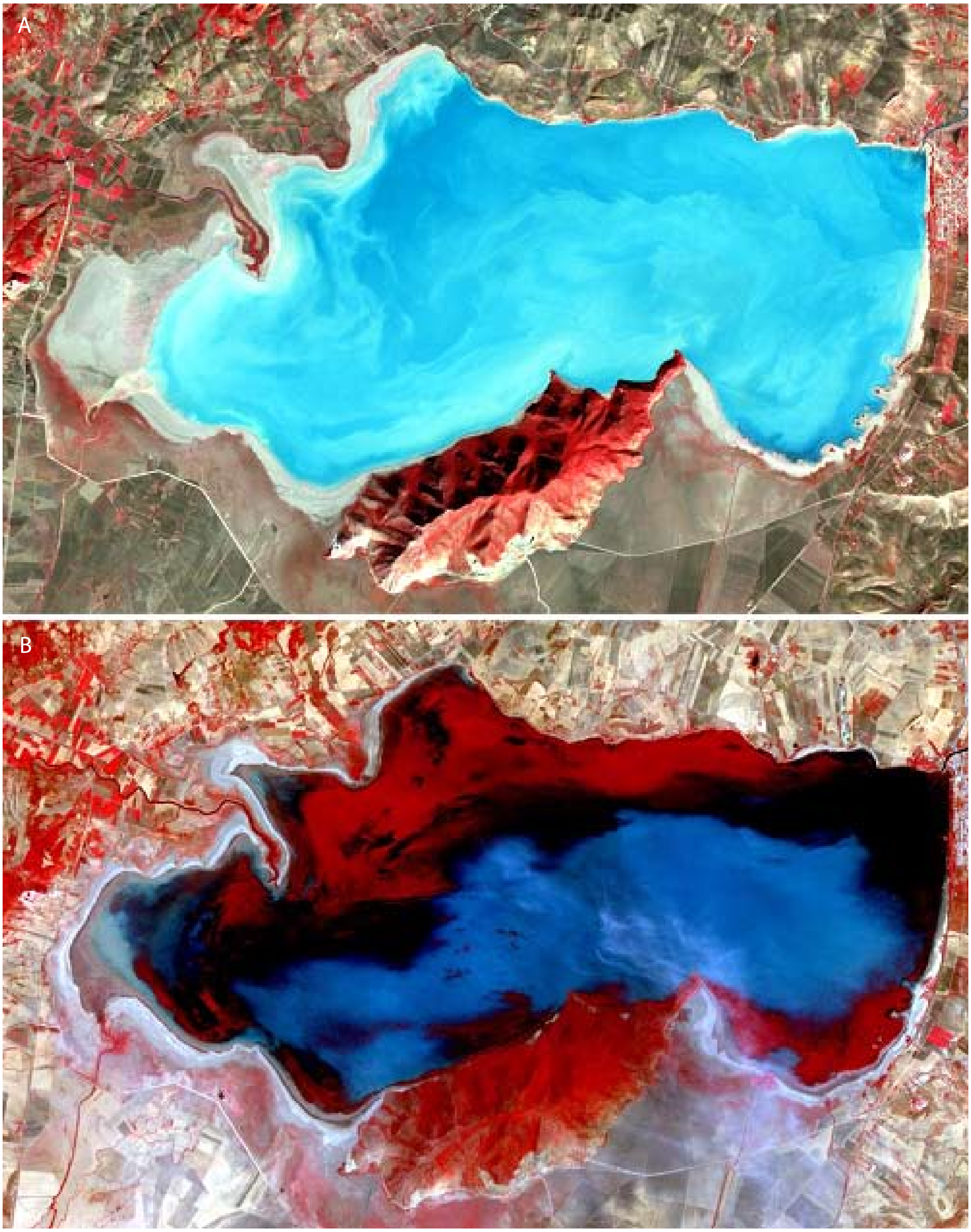


FIGURE 3.2 False colour composite. False colour composites of Ichkeul Lake in Northern Tunisia A November 14, 2001 and A July 29, 2005. Vegetation on land and in water is indicated by shades of red as infrared reflectance is passed through a red colour filter within an image processor. Dam construction in the region has drastically reduced the inflow of freshwater to the lake causing an increase in salinity and a replacement of reed beds, sedges and other fresh-water plant species by halophytic (salt-loving) plants, thereby diminishing critical stopover habitat for migrating birds. Source: NASA/GSFC/METI/ERSDAC/JAROS and U.S./Japan ASTER Science Team.

shading, which, in turn, strongly affects reflectance from that canopy back to the sensor. For example, tall forests tend to appear darker than shorter forests because of greater canopy shading with increasing tree height. Variable tree height can also increase shadowing. The combination of reflectance properties allows for the differentiation between many vegetation types with satellite imagery, and these vegetation types are often good indicators of (or surrogates for) land cover or habitat type.

The sensors discussed thus far are referred to as "passive" because they rely solely on capturing reflected light emitted from the sun. There is another major class of sensors called "active"; these sensors emit a pulse energy off a surface and then capture the return to the sensor. Two increasingly popular active sensors include radar and lidar. Radar sensors, which emit microwave pulses, are a more established technology than lidar sensors, which emit laser pulses. Both sensors are particularly useful in mapping forest characteristics, including age, density, and biomass. In radar images, different forest types also have different detailed textures (spatial patterns of variability produced by objects too small to be detected individually), which result from the amount of variation in canopy height as observed from above (Saatchi et al. 2000). Radar signals are sensitive to water and wet soils, thus radar is also valuable for tracking spatial and seasonal patterns of flooding.

Radar is even more valuable when more than one wavelength is used, because energy in shorter wavelengths tends to bounce off small and large branches and leaves, and energy in longer wavelengths tends to bounce off only larger branches. A major advantage of radar is that it can penetrate clouds. A major disadvantage is that it is very difficult to use in vegetation mapping in hilly or mountainous areas because the topography dominates the patterns observed. Also, radar satellites are currently not multispectral (they record in only one spectral region), and the data are relatively expensive compared to most optical satellite data. Although the use of both radar and lidar is increasingly common for specific mapping needs (such as mapping forest density and age or the use of radar in cloudy regions of the world such as the humid tropics), these technologies are still in development and products generated from passive optical sensors are often more appropriate for operational monitoring for the near future. For these reasons, the bulk of this book addresses applications with optical imagery.

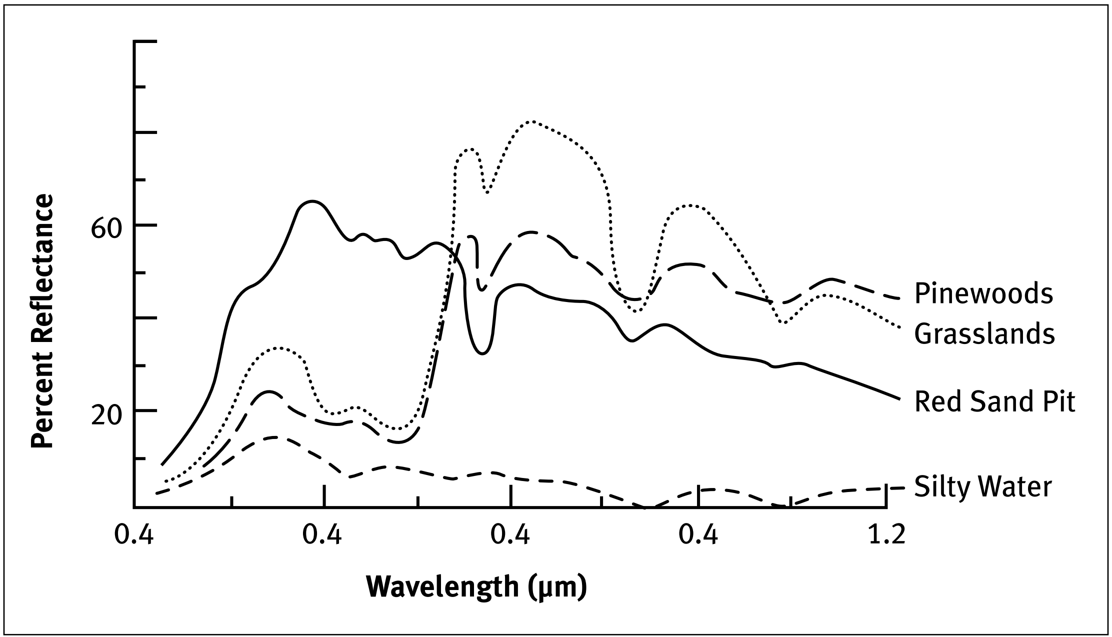


FIGURE 3.3 Spectral curves for various natural features Source: NASA remote sensing tutorial available at http://rst.gsfc.nasa.gov (accessed December 2006).

3.4 Issues that affect selection of images

Remote imaging sensors can differ in many ways. Most satellite and airborne sensors produce digital images from several spectral bands, each band corresponding to a specific wavelength range within the electromagnetic spectrum. The sensors discussed in this chapter focus on the visible and infrared wavelengths.

The main characteristics of a sensor of importance to the user include:

- image size or path width
- region of the earth from which images are acquired
- spatial resolution (the size of the unit at which data are collected)
- number of bands and wavelengths detected
- frequency of image acquisition
- date of origin of the sensor.

3.4.1 Image size (path width)

The area covered by a single satellite image is defined by the path width and the distance of the satellite along its path. The path width is limited by how far to each side of the sensor's center reflected light from the earth's surface can be collected. The path width can vary from as little as 8 to more than 2,000 kilometres. Larger image sizes usually correspond to a coarser spatial resolution; however, it is easier to work with fewer images because mosaicking them (combining them into one large image) is time consuming and can introduce inconsistencies. These inconsistencies can occur because each image is taken under specific environmental conditions, meaning that the same feature on the ground can produce a different reflectance based on various parameters, including humidity, cloud cover, and time of day. Spatial resolution is discussed further below in section 3.4.2.

Most Earth-observing satellites orbit from pole to pole in a sun-synchronous orbit, allowing the sensor to cross the equator at the same time — usually in the mid-morning for the daylight half of its orbit and in the evening for the other half of its orbit. Areas close to the poles might not be covered at all with sun-synchronous sensors. Most remote sensing satellites have a near-polar orbit and are not able to acquire imagery directly at the poles because their orbit does not go over these areas. Another class of satellite sensor is geostationary, which appear to remain stationery over a point on the ground. These satellites monitor large areas of the Earth's surface and they track the Earth's rotation so the satellite sensors are able to continually view the same area of the ground. This is a common orbit for weather satellites.

3.4.2 Resolution (spatial, temporal, spectral, and radiometric)

Several different characteristics affect the detail that can be resolved (seen) in an image. These are traditionally referred to as the four types of image resolution. Most people think of "resolution" as being synonymous with spatial resolution, but these other "resolution" terms are used in the formal literature and directly affect our ability to monitor any given object or phenomenon.

Spatial resolution, which is often referred to as simply "resolution," is the size of a pixel (the smallest discrete scene element and image display unit) in ground dimensions. In most cases, an image's resolution is labelled with a single number, such as 30 metres, which represents the length of a side of a square pixel if it were projected onto the Earth's surface. If the pixel were rectangular, then both the height and width of the pixel would be provided. Along with spatial resolution, it is useful to be aware of the minimum mapping unit, which is the minimum patch size included in a map. This differs from the sensor resolution, because maps usually have been filtered after classification (discussed later in this section). For example, a map produced from 30-metre resolution data may have been filtered so that there are no patches in the map that are smaller than 5 hectares.

Positional accuracy with reference to known locations is a concept correlated with spatial resolution. Are the estimated locations of vegetation boundaries accurate to within 1 kilometre or within 100 metres or more? For the GLC2000 global-scale data set, for example, positional accuracy had a reported error of 300 metres (Mayaux et al. 2006). Positional or locational accuracy is generally better for more recently acquired satellite images than older images, because the processing used to assign geographic position to raw satellite images (called ortho-rectification) has dramatically improved over time.

Repeat frequency or temporal resolution is the minimum time scale during which a particular feature can be recorded twice. For example, with Landsat, the same image area can be recorded every 16 days, because this is the length of time it takes for the satellite to complete one complete path over the Earth. Some sensors with a very wide field of view can acquire multiple images of the same area in the same day. Although most sensors are static within the satellite, some can be pointed (within limits) at particular features as needed. This can reduce the repeat frequency for which a feature can be recorded. Ecosystem-specific regeneration rates are one of the important considerations when determining desired temporal resolution of remote sensing data (Lunetta et al. 2004). Early warning systems for sudden loss of habitat—such as by fire or illegal logging—may require daily to weekly acquisitions.

Spectral characteristics include band width, band placement, and number of bands. Spectral bandwidth—or spectral resolution, as it is often called—is the range of wavelengths detected in a particular image band. Band placement defines the portion of the electromagnetic spectrum used for a particular image band. For example, one band might detect blue wavelengths and another might detect thermal wavelengths. The particular properties of the features of interest indicate which bands are relevant for a given application. The number of bands is generally less important for visual interpretation or viewing, because an analyst can view only three bands at a time. Multiple bands are more important for using automated classification approaches. Hyperspectral sensors slice the electromagnetic spectrum into many discrete spectral bands (usually more than 100). This can enable the detection of spectral signatures that are characteristic of certain plant species or communities. However, analysis of hyperspectral imagery is still a new, developing field.

A sensor records the intensity of a given wavelength as a single whole number between the minimum and maximum of a range. For example, Landsat TM sensors can store values from 0 to 255, whereas IKONOS sensors can store values from 0 to 2,048. This potential range of values is often referred to as radiometric resolution. The number of values that can be stored limits the amount of variation within a wavelength band that can be detected, which is one aspect of sensitivity.

Sensitivity is also defined by the sensor's dynamic range. Sensors of particular wavelength bands have extremes of sensitivity above and below which they cannot differentiate change in intensity. If the signal returned for a particular band is too faint, then the sensor cannot record it; conversely, if a signal is greater than the maximum recordable by the sensor, it is saturated and cannot record any further change above this level.

Monitoring or assessment programmes may require a certain level of thematic precision, which refers to how many specific categories (such as vegetation types) are represented. There is some desire to understand trends for very specific types of vegetation cover types—for instance "seasonally inundated *Mauritzia* palm forest." But accuracy is usually higher when mapping broader types, such as "all humid forests." It is sometimes desirable to distinguish between different stages of regeneration (or age), especially for forest ecosystems. The degree to which remote sensing data can be used to estimate these stages varies by biome, but in all cases, estimation of area within specific age classes is always less accurate than the estimation of the area of all ages combined. Therefore, before determining the level of precision required for indicators, the implications for expected accuracy in reported trends should be considered. The level of potential thematic precision is maximized when data of high spatial, temporal, and spectral resolution are used.

3.4.3 Image availability

A.3 and A.4 in the Appendix includes links to available satellite imagery that could be used for monitoring land cover and habitat distribution. Of the large number of potential image types, only a few are practical for monitoring over entire countries because most are either costly or have too small a data archive, especially outside the range of the country that launched the satellite.

The most practical data sources for biodiversity monitoring are those that record data in the areas of the spectrum from infrared through the visible bands to ultraviolet. Landsat data have been the most heavily used because of their relatively fine spatial resolution (30 by 30 metres) and moderate cost. SPOT HRV images are of similar quality to Landsat, have a pixel size of 20 by 20 metres, and are fairly well archived; however, their cost can be prohibitive for many national assessments. Recent data collected from comparable Brazilian, Chinese and Indian satellites at similar spatial resolutions are also useful when available. However, these latter sources have smaller collections of archived data.

Other useful data are collected at coarser spatial resolutions, such as 250 metres to 1 kilometre. Some of the best-known sources of coarse-resolution data for habitat monitoring are NASA's MODIS sensors and SPOT Vegetation data, coordinated by the Vegetation Programme. These data are usually free, well archived, and available soon after acquisition. However, they are not optimal for monitoring habitat extent, fragmentation, and rates of change. In most areas, changes occur in many small patches that are more detectable with finer-resolution imagery. Conversely, coarse-resolution imagery can be processed quickly and can therefore provide a valuable complement to finer-resolution data. The availability of both types of data means that countries can maintain a monitoring system in which coarse-resolution imagery can be used to estimate change as part of an early warning system, and finer-resolution data can be analysed less frequently to produce condition and change assessments of greater precision.

Imagery is also available at very high spatial resolutions—five metres or finer. These data are provided by private satellites and are usually very expensive. However, they are perhaps the only option, other than repeated aerial or field surveys, for monitoring certain small-size ecosystems or habitats. These may include waterbodies such as small rivers, lakes, wetlands, and some mangroves and coral reefs. It would be costly to conduct nationwide monitoring of these habitats with such data; however, these data may be useful in a sample-based approach complemented with field or aerial surveys.

3.4.4 Relationships among image size, resolution, and image availability

Wide paths tend to be associated with low spatial resolution and are linked to shorter repeat cycles, thus increasing the temporal resolution. A high spatial resolution is linked to large data volumes, which increase the time needed to manipulate and analyse the images. These issues can lead to trade-offs between spatial, temporal and spectral resolution.

To achieve high spatial resolutions, some sensors have a panchromatic band, which has great spectral width, including much of the visible and near-infrared portion of the electromagnetic spectrum, and high spatial resolution. For example, the panchromatic band on Landsat 7 ETM+ sensor is 15 metres; the other bands are 30 metres or greater. The panchromatic band can be incorporated with other bands to enhance the visual sharpness of the image, which is valuable for mapping some important habitat types.

3.5 Image classification

There are various approaches and quantitative methods for using remote sensing data to discriminate different types of habitat cover. These are broadly called classification methods, and some of the more common ones are presented as case studies in this book. Two broad types of classification method are *supervised* and *unsupervised*.

In supervised classification, the analyst defines areas where the land cover or habitat type is known to occur. Parameters and statistics are then derived from the satellite imagery for these defined areas (or training sites). These parameters and statistics relate to the spatial reflectance values of the particular land cover types and habitats and include the mean values and covariance (the extent to which two variables vary together) from different wavelength bands for each area. These parameters and statistics are then used to estimate what the cover type is most likely to be for all parts of the image that have not been predefined. The process of defining the known areas of cover and calculating the spectral statistics is called training and is usually carried out by drawing polygons over parts of the image for which land cover type is known and labelled as such, followed by the automated calculation of the statistics by the image processing software.

In an unsupervised classification, the analyst does not predefine the land cover or habitat types. The image processing software divides the image into a certain number of classes, based entirely on the spectral data and with no knowledge of what cover types are present in the image. The user can define limits to the number of output classes and spectral variance within each class. The resulting classes are identified by different numbers, and the analyst must then assign names to these classes with the support of field knowledge and an understanding of how different habitats should appear in these images.

In both supervised and unsupervised approaches, several iterations are usually conducted before a classification is completed. In supervised classification, this usually involves modifying the training data. In unsupervised classification, it usually requires selecting any ambiguous classes and rerunning the analysis to split the classes into a larger number of subgroups that are then labelled separately with known cover types.

More advanced methods of classification include such things as binary decision trees and neural networks, which are currently not available as part of most standard software programs. In these approaches, classification can be *per pixel*, in which only the spectral data for each individual pixel are used to classify it, or *contextual* in which data from neighboring cells can be included to assist classification of each pixel. Some contextual classifiers use information about the texture (spectral variance) around a given pixel.

In all classification methods, the resulting image is often speckled, with individual, isolated pixels of one class surrounded by pixels of another. For this reason, filters are usually applied to the final classifications to smooth or generalize the final classification result. Neighborhood filters are often used. An example of a neighborhood filter is the majority filter, which reassigns the value of a central pixel to the value of the majority of cells around it. The effect eliminates very small clusters of pixels of the same class while it smoothes edges between groups of pixels of differing classes. Other filters act as sieves—small patches of pixels of the same class are reclassified, but large ones are not. This eliminates small patches without modifying the edges between larger, unfiltered patches. The analyst must make a decision as to the type and level of filtering applied based on knowledge and desired result, which has consequences for the quality, accuracy, and applicability of the final product.

Change in land cover may be assessed by direct analysis of the raw satellite data from different dates or in a postclassification comparison in which two classified maps from different dates are compared to each other. Estimates of change from the latter technique tend to have greater errors because of differences in interpretation during the classification process for each image date. The better approach is to directly map changes from the raw satellite data collected from the different times. Precise coregistration of images (making sure the same pixels from different acquisition dates overlay each other precisely) is necessary for accurate estimation of change when using this technique. It is usually possible to attain a precision of less than one pixel width.

Postclassification comparisons based on supervised classification, unsupervised classification, decision trees, and neural networks have all been successfully applied to the process of mapping changes in vegetation cover over large areas, and all are capable of producing similar results. The key to conducting accurate postclassification comparisons is consistent interpretation of the images used. This is especially important if there are many images to analyse and more than one analyst involved. Care must be taken to ensure that the areas that have not changed over time are being interpreted consistently.

Collection of independent information to assist interpretation of the images, and to conduct an error assessment of the final product, is also important and necessary. This information is increasingly being collected by aerial surveys. The cost of surveys is not as prohibitive as field sampling, and aerial surveys can generate excellent observations over an entire country in a short time. Digital aerial photography and videography are very valuable, especially when the photos and video frames can be automatically linked geographically. Because small features can be easily seen in these images, they provide an excellent source of data to assist satellite image interpretation and validation of final classified maps.

3.6 Additional issues to consider

Like any monitoring tool, remote sensing has advantages and limitations. The main advantages are that large amounts of uniform data can be collected from a distance, remote sensing can cover extensive areas, and remote sensing is less expensive than field-based mapping efforts. Constraints include technical limits on feature discrimination; costs (although cheaper than field-based assessments, they can still be prohibitive); the requirement of high levels of technical expertise; and the need for information to calibrate and verify remote sensing results, which can be limiting (Turner et al. 2003).

3.6.1 Technical limits of remote sensing technology

For most sensors, remote sensing can monitor only features that can be viewed from above; characteristics of the understory must be inferred rather than directly observed. Lidar and radar sensors are exceptions, but as mentioned earlier, these technologies pose other constraints, including cost, lack of analytical monitoring standards, and data availability.

When classifying remote sensing data to produce a map of vegetation, the individual features belonging to a particular class of interest must be large with respect to the resolution of the imagery. For example, a stream that is 10 metres wide could not be detected in an image composed of cells of 1-kilometre spatial resolution. In addition, and crucially, the feature being observed must have a sufficiently unique spectral signature to be separated from other types of features. For example, it may be difficult to distinguish secondary from primary forest without additional supporting data.

Atmospheric phenomena, mechanical problems with the sensor, and numerous other effects can distort the input data and therefore the results, although algorithms and models to correct these distortions are improving continuously. Cloud cover is the most common impediment to seeing the earth's surface with optical sensors and is particularly problematic in some regions of the world where cloud cover is common (for example, wet tropics). Haze and thin clouds are less problematic, but can result in distortions of feature spectral signatures, resulting in greater error or more expensive and complex processing.

Further reading on this topic can be found in a guide to "Myths & Misconceptions in remote sensing" (http://cbc.rs-gis.amnh.org/remote_sensing/guides/basic_concepts/myths.html) published by the American Museum of Natural History.

3.6.2 Cost-effectiveness of remote sensing[1]

Using remote sensing in combination with field surveys is likely to be the most cost-effective solution to monitoring the status of many aspects of biodiversity at regular intervals. This is especially true for the monitoring of large areas. Since the total cost is likely to be considerable; there must be clearly defined needs and users for the resulting information. According to Mumby et al. (1999) four types of costs are encountered when undertaking remote sensing: (1) set-up costs, (2) field survey costs, (3) image acquisition costs, and (4) the time spent on analysis of field data and processing imagery. The largest of these are set-up costs, such as the acquisition of hardware and software. This may make up 40–72 percent of the total cost of the project, depending on specific objectives. Fortunately, increases in computational power are driving down the costs of associated hardware and software. If set-up costs are fixed—that is, if remote sensing hardware and software already exist—then field survey costs will dominate the project budget at approximately 80 percent of total costs (or 25 percent with set-up costs). Field survey is a vital component of any habitat-mapping programme and may constitute approximately 70 percent of the time spent on a project. In general, the more time and effort spent on field surveying and ground-truthing, the higher the accuracy of the resulting product.

The third major cost is imagery. The selection of imagery is made considering the trade-offs between map accuracy and the cost of imagery; the latter depends on the size of the study area and choice of sensor. SPOT XS is a cost-effective satellite sensor for mapping an area that does not exceed 60 kilometres in any direction (that is, it falls within a single SPOT scene). ASTER is also economical but new acquisitions must be requested ahead of time online. For larger areas, Landsat TM is a cost-effective and accurate sensor. MODIS is free thus far, but it has a short historical record and is suitable only for coarse-scale regional monitoring. The relative cost-effectiveness of digital airborne scanners and aerial photography are more difficult to ascertain because they are case specific. Generally, the acquisition of digital airborne imagery is more expensive than the acquisition of colour aerial photography. However, this must be offset against the huge investment in time required to create maps from aerial photograph interpretation. After data are acquired, technical expertise will be needed to process and analyse the imagery, and this is likely to cost more in salaries than the imagery or hardware costs. And finally, to establish a successful monitoring programme entails repeated measurements of both biodiversity indicators and habitat, all except set-up costs are likely to be recurrent (Turner et al. 2003).

3.6.3 Technical expertise

One challenge for ecologists and conservation biologists hoping to incorporate remote sensing technologies into their work is to acquire or co-opt the technical expertise required to handle and interpret the data. Managing even small quantities of satellite imagery requires specialized software, hardware, and training. The expertise and equipment often exist in-country, but not necessarily within the agencies with an interest in biodiversity monitoring. Fortunately, new software tools are making remote sensing data more accessible to nonspecialists, and the possibilities for training are growing rapidly. The Appendix includes a list of online tutorials covering specific areas.

Some remote sensing platforms (for example, hyperspectral, lidar, and radar) are largely or exclusively in the research phase of development and may not be in common use for some years. The number of experts who can work with these platforms is likely to grow in the future.

1 This section adapted from Mumby et al. [1999]

3.6.4 Requirement for calibration

A 2010 indicator monitoring plan should therefore consider means of fostering collaboration among remote sensing researchers and fieldworkers in biodiversity science and conservation. Ecologists, evolutionary biologists, and conservation biologists may have useful data sets on distributions of individual species, species richness, and endemism that would help to derive biodiversity indicators. The expertise to link these biodiversity data with global, regional, and local data sets—such as land cover, primary productivity, and climate—may be found in remote sensing laboratories within universities, other institutions, or consultancy firms. These connections among disciplines are emerging around the world, with existing remote sensing laboratories taking an interest in biodiversity and biodiversity specialists beginning to include remote sensing and GIS expertise in their own professional toolkits.

3.7 References

Lunetta, R. S., D. M. Johnson, J. G. Lyon, and J. Crotwell. 2004. Remote sensing of environment impacts of imagery temporal frequency on land-cover change detection monitoring. *International Journal of Remote Sensing* 89(4):444–54.

Mayaux, P., A. Strahler, H. Eva, M. Herold, A. Shefali, S. Naumov, S. Dorado, C. Di Bella, D. Johansson, C. Ordoyne, I. Kopin, L. Boschetti, and A. Belward. 2006. Validation of the Global Land Cover 2000 map. *IEEE Transactions on Geoscience and Remote Sensing* 44(7):1728–39.

Mumby PJ, Green EP, Edwards AJ, Clark CD. 1999 The cost-effectiveness of remote sensing for tropical coastal resources assessment and management. *Journal of Environmental Management* 55:157-166

Saatchi, S.S., B. Nelson, E. Podest, J. Holt. 2000. Mapping land cover types in the Amazon Basin using 1 km JERS-1 mosaic. *International Journal of Remote Sensing* 21(6-7): 1201-1234.

Short, N. M. Sr., NASA remote sensing tutorial. http://rst.gsfc.nasa.gov (accessed April 12, 2007)

Turner, W., S. Spector, N. Gardiner, M. Fladeland, E.J. Sterling and M. Steininger. 2003. Remote sensing for biodiversity science and conservation. *Trends in Ecology and Evolution* 18(6):306–314.

Chapter 4. Trends in Selected Biomes, Habitats, and Ecosystems: Forests

AUTHORS: James Strittholt[1], Marc Steininger[2]
CONTRIBUTORS: Colby Loucks[3], Ben White[4]
REVIEWERS: Mette Løyche Wilkie[5], Manuel Guariguata[6]

1 Conservation Biology Institute, 2 Conservation International, 3 World Wildlife Fund (WWF-US), 4 Global Land Cover Facility, University of Maryland, 5 Food and Agriculture Organization of the United Nations, 6 Center for International Forestry Research

Remote sensing based indicators for forests:

- Extent of component ecosystems
- Forest change
- Rate of deforestation/reforestation
- Forest intactness
- Area and number of large forest blocks
- Forest fragmentation
- Carbon storage
- Area and location of old-growth forests
- Area and location of plantations
- Forest degradation
- Area and location of sustainable forestry
- Alien species
- Fire occurrence

The physical characteristics of forest ecosystems reflect sunlight in the visible, near-infrared, and middle-infrared regions of the light spectrum in ways that are easily distinguished from other types of vegetation cover. Thus, remote sensing has become an important tool for evaluating forest ecosystems at multiple spatial and temporal scales to examine and monitor forest composition, structure, and function (Kerr and Ostrovsky 2003).

4. 1 Delineating Cover and Estimating Change in Extent

Leaves are full of pigments that absorb visible light. Therefore, because of their dense leaf cover, forested areas tend to reflect less light from the visible region of the spectrum (and thus appear darker than) other vegetation types. In contrast, leaves strongly reflect near-infrared light — which is not visible to our eyes — and thus they appear brighter when near-infrared data are mapped. Water in forest leaves absorbs near-infrared light, and thus forests tend to appear dark when middle-infrared images are displayed. The middle-infrared is also best able to reveal "canopy shading." This is caused by the canopy geometry (i.e., the uneven tree and branch height) of forests. In general, taller forests with more uneven canopies, such as old-growth forests, appear darker in the middle-infrared than shorter forests with more even canopies, such as young secondary regrowth, because of a combination of canopy shading and the water absorption of leaves. This darkening trend is also seen in the near-infrared, although less so. Inundated forests usually appear even darker still, because of even more light absorbed by standing water or wet soils beneath the canopy. The brightness in all of these spectral regions also depends on the colour of the background underneath the canopy, which is a mix of soil and vegetative litter. The influence of the background colour is more obvious when leaf cover is lower, such as in areas of more open vegetation during the dry seasons when leaves have senesced.

When observing optical images of forests and other types of vegetation cover, it is useful to consider how green they are (leaf cover), how bright they are (canopy shading), and how wet they are (inundation). As an example, we can consider the changes in reflectance in these three spectral regions as a forest regenerates, developing from mostly shrub cover with relatively little leaf cover and an even canopy to mostly young trees with more leaf cover and a somewhat even canopy and then to a tall forest with maximum leaf cover and a very uneven canopy (Moran et al. 1994; Steininger 1996). As a forest grows, the visible reflectance declines rapidly to as low as 5 percent when leaf-area indices are 4 or greater. Near-infrared reflectance increases in the early stages of regrowth because of increasing leaf cover, but then often decreases somewhat at later stages of regrowth because of canopy shading. Throughout the regrowth sequence, middle-infrared tends to gradually decline. Depending on the type of forest and the rate of regrowth, older secondary forest regrowth begins to appear similar to old-growth forest.

Another characteristic of optical images, at least those at finer spatial resolutions, is the texture of the image. Images of some forest types appear speckled or mottled. For example, a tall tropical forest appears speckled in Landsat images because the spatial resolution, 30 metres, is close to the size of a single tree crown. Thus one pixel may image a tree crown (bright in near-infrared), and its neighboring pixel would image a shaded gap in between two crowns (dark in near-infrared). In a coarser image, such as a MODIS reflectance image, this same forest would appear smooth. A mottled texture in a Landsat image, in which the image appears to have small clumps of several pixels that are brighter than neighboring clumps, may indicate a logged forest that has gaps the size of several tree widths.

Global maps from 0.5-kilometre to 1-kilometre resolution satellite data already provide a reasonable snapshot of the general extent of forest cover. The Global Land Cover 2000 (Bartholomé and Belward 2005) map product was based on 1-kilometre spatial resolution satellite data acquired over the whole globe by the VEGETATION instrument on board the SPOT 4 satellite). The GLC2000 product includes eight forest classes: (1) broadleaved, evergreen; (2) broadleaved, deciduous, closed; (3) broadleaved, deciduous, open; (4) needle-leaved, evergreen; (5) needle-leaved, deciduous; (6) mixed leaf type; (7) regularly flooded, fresh water; and (8) regularly flooded, saline water (Bartholomé and Belward 2005). The reported overall accuracy of this product is greater than 70 percent (Mayaux et al. 2006). A similar product, the Global Land Cover Characteristics Database (GLCCD), was created from a 1-kilometre spatial resolution Advanced Very High Resolution Radiometer (AVHRR) and likewise contains coarse-level forest classes (Loveland et al. 2000).

The coarse spatial resolution of these global products provides a useful, general baseline of forest cover by general forest type, but they are not suitable for global or national forest operational monitoring because of insufficient accuracy and the lack of detailed forest themes. For example, small nonforest patches within forest dominated regions and small forest patches in low forest regions remain undetected with coarse sensors, leading to over- and underestimation of forest extent. Some of this error can be reduced by calibration against high-resolution data (Mayaux and Lambin 1997), but with the widespread availability of moderate- and high-resolution sensors, it is better to conduct national and subnational forest mapping using these higher resolution platforms. For not only is spatial accuracy of forest extent enhanced, but also these sensors allow for better discrimination of forest types and other characteristics such as forest age.

Spatial resolution is enhanced at the global level with more refined sensors like MODIS (250- to 500-metre spatial resolution) and MERIS (300-metre spatial resolution), which were developed to facilitate global change assessments. The MODIS land cover product used a supervised classification approach in which training sites were provided using a decision-tree classifier (Friedl et al. 2002; McIver and Friedl 2002). Map accuracy for version 3 of this global-mapping product has been reported to be 75–80 percent overall; 70–85 percent by continental regions; and 60–90 percent for individual cover classes (Friedl

2007). MODIS Vegetation Continuous Fields (or Percent Tree Cover) has provided additional land cover detail specific to forests (Hansen et al. 2003), advancing our ability to map forests at the global level with greater precision and accuracy.

These coarse spatial resolution products have considerable value at the global scale, but they lack sufficient thematic and spatial detail needed for habitat assessments on the level of individual countries, and the spatial resolution is too coarse for a basis for high-quality forest-change monitoring. Nevertheless, technical remote sensing capabilities have advanced dramatically over the past decade, and monitoring forests at the national level is now a feasible goal for most countries (Mollicone et al. 2003; DeFries et al. 2006).

Moderate resolution sensors, including Landsat, ASTER, SPOT HRV, and IRS with spatial resolutions from 15 to 60 metres have formed the foundation for forest mapping at the national and subnational level. Numerous examples of results (many available online) from these efforts are provided in the resource section at the end of this chapter. For most nations, employing these sensors to conduct their forest monitoring needs provides the most cost-effective method, with reasonable thematic and spatial accuracies (usually greater than 80 percent) routinely observed. Also, there is a growing digital image library for many of these sensors, allowing for informative change detection assessments and trends analyses.

There are newer, high-resolution optical sensors (5-metre resolution or less) now being used to map and evaluate forest ecosystems. A number of airborne sensors collect digital imagery at multiple spectral bands such as CASI (Anger et al. 1994), as well as satellite platforms such as IKONOS and QuickBird. These sensors often provide enough spatial and spectral detail to map individual trees. High-resolution remote sensing plays a minor or nonexistent role when monitoring forests at the global or national scale: high-resolution imagery is generally cost-prohibitive from the standpoints of both data acquisition and handling. However, particular forest community types or individual tree species of global importance that are distinctive (e.g., *Dipterocarpis* spp. in Thailand and *Doona congestiflora* in Sri Lanka) could be monitored using these technologies.

Active remote sensing systems (radar and — to a lesser extent — lidar) are emerging as the new generation of forest remote sensing tools because they provide a number of advantages over optical systems: (1) ability to collect data in regions of continuous cloud cover; (2) usefulness in tracking forests that are seasonally inundated by water; (3) better estimates of forest biomass because they provide a 3-D perspective of the forest; (4) help in the classification of stand age; and (5) measurement of subcanopy characteristics (Wulder et al. 2004). Like all remote sensing technologies, active sensors have technical disadvantages as well (e.g., radar does not perform particularly well in hilly terrain), and much more research is needed before we realize the full benefits. Active remote sensing is still cost-prohibitive for large areas such as many national assessments, but may have a place in a global-/national-monitoring context in the near future or for special cases today. Finally, researchers are exploring data integration for mapping forests. For example, by combining Landsat Thematic Mapper imagery with lidar (Lefsky et al. 2002) or radar (Treuhaft et al. 2004), a third dimension to otherwise two-dimensional forest mapping can be achieved.

4.1.1 Mapping humid tropical forests

Under ideal conditions, mapping forests using remote sensing is reasonably accurate and cost-effective. However, different forest biomes pose unique challenges to remote sensing. The most obvious technical issue for humid tropical forests is the difficulty in obtaining clear images of regions that are persistently cloudy, such as most rainforest and almost all montane, submontane, and island forest regions. In mountainous areas, rugged topography adds further complexity to image interpretation, primarily because of shading, which in some areas can be quite severe. Because optical sensors rely on reflected light, shaded areas reflect little or no light back to the sensor, resulting in little or no reflectance data used to discriminate different cover classes. Under variable illumination conditions, the same forest type appears differently in satellite images, depending on whether the forest is on the sunlit or shaded side of a mountain. Under heavy shading conditions, as much as 10–25 percent of a region can be lost or compromised by shadows.

4.1.2 Mapping dry tropical forests

Because of their heterogeneous pattern, loss of leaves in the dry season, and variability of the tree canopy, tropical dry forests are susceptible to misclassification without validation with ground information. Great care should be taken in choosing when satellite images are acquired: — both wet versus dry seasons as well as the particular conditions during any given year. Ideally, for each time period of interest, two sets of images — one from the end of the wet season and one from the end of the dry season — should be processed. This will allow for the mapping of forest extent (end of wet season imagery) and the degree to which the forests retain their leaves (end of dry season). From this information, it is possible to assess the percentage of canopy cover and to better separate the region into discrete classes based on spectral reflectance.

Also, many dry forests frequently burn as the dry season progresses and may begin to resemble bare lands or dry agricultural fields during this period. This underscores the need for a wet season image, which will clearly demonstrate the extent of forests, agricultural areas, and residential areas.

Degraded areas, often found in the wetter, more semievergreen dry forests, may resemble mixed deciduous forests in satellite data. Also, care should be taken to properly assess areas that have been degraded against those areas that have a natural open canopy system. One clue is that degraded areas are more likely to be found closer to human settlements or roads. Dry season imagery may contain open canopies, but also an understory filled with vegetation such as bamboo. Riparian forests will likely be similar to evergreen or mixed deciduous forests, especially in a dry-season image. It is likely that they contain different tree species, despite the similarity in phenology.

4.1.3 Mapping boreal and temperate forests

The overall principles for interpreting optical images of forests for brightness, greenness, and wetness apply to both temperate and boreal forests. For boreal forests, it can be particularly useful to estimate varying levels of inundation because many of the boreal forests are closely associated with extensive wetlands. Boreal forests are also characterized by cycles of forest regeneration resulting from recovery following wildfires and logging. Thus, estimating the age, height, biomass, or stage of regeneration can be important. The rate of forest growth is slower in the boreal zone than in other zones, so it takes longer for secondary forests to appear similar to mature forests. This is further emphasized by the typical succession from shrubs to broad-leaved trees to needle-leaved trees. The different shapes and distributions of leaves in canopies mean that broad-leaved forests tend to appear much brighter and greener than needle-leaved forests. In the boreal context, areas that appear brightest and greenest can be either mature hardwoods or early regenerating conifer stands, which are often mixed with deciduous species.

Remote sensing using finer-resolution sensors (e.g., Landsat and ASTER) is the most effective and economical approach to mapping boreal forest communities (e.g., black spruce, jack pine, and larch) that would be most meaningful for biodiversity purposes, but because of a relative lack of commercial interest in the more remote regions of the boreal, it has not been a high mapping priority for Governments. However, this is changing as human development rapidly encroaches into the undeveloped regions of the boreal zone. Community-level data is important for two reasons: (1) some boreal forest types are rarer or more threatened than others (e.g., riparian white spruce forests and white pine forests), and these communities should be monitored more carefully; and (2) the goal of representing biodiversity in a system of global protected areas can be achieved only when we know the extents and conditions of the different forest communities.

Mapping the extent of temperate deciduous forests can be accomplished with high levels of accuracy when there is high contrast between the forest and other cover types. It becomes more challenging when forest and shrublands are intermixed. In drier regions, deciduous forest may gradually transition to open woodlands, and it is difficult to consistently define a border between the two. Furthermore, the season of the year and different precipitation levels can make appearance of both forest and shrublands vary dramatically. The best way to distinguish varying levels of deciduousness, to characterize gradients of forest and woodland types, is to analyse images from different seasons.

4.1.4 Change in forest extent

An important source for forest change information is the United Nations Food and Agriculture Organization (FAO) series of Forest Resources Assessments (FRAs) produced from national data. FRA 2000 and FRA 2005 are the two most recently published reports, with another one planned for 2010. FRAs have traditionally been produced using field data; however, FRA 2000 included an assessment of forest area changes in the tropics based on remote sensing. Increased use of remote sensing technologies is being promoted for the next Forest Resource Assessment report scheduled for 2010 (FAO 2006). It is anticipated that the FRA for 2010 will include an analysis of a sample of Landsat data (30-metre resolution data): a 10-kilometre by-10-kilometre sample of multi-temporal images (1975-1990-2000-2005) located at every 1-degree-by-1-degree latitude/longitude intersection (FAO 2006). These new estimates should provide more accurate and consistent results and should represent one of a suite of global estimates of trends using varying sources of satellite data.

Despite very different data sources and methods, estimates of the global rate of deforestation during the 1990s derived from remote sensing, and FAO results derived largely by other means agree to within 15 percent. This is encouraging for global research. However, the level of agreement declines when these products are compared at the continental level or for shorter time periods. For example, the same estimates show a 40 percent disagreement at the continental level (Global Observation of Forest and Land Cover Dynamics [GOFC-GOLD] 2004). The estimates of deforestation rates for individual countries reported to FAO can differ by as much as 100 percent from estimates derived from wall-to-wall mapping with moderate-resolution data (Tucker and Townshend 2000; Steininger et al. 2001). Much of this disagreement is attributable to the following three factors: 1) inability to detect small area changes with medium to coarse resolution remote sensing, 2) inadequate resources and capacity to collect timely and comparable national-level information over time – especially in Africa, and 3) differences in the definition of "forest"– partly related to the choice of methodology both between countries and over time within countries. The latter problem reinforces the importance of clear standards and the clear understanding of definitions and data-handling methods.

Other examples of global forest change efforts include (1) a coarse resolution (8-kilometre resolution product) created by the University of Maryland (Hansen and Defries 2004); (2) a global sample of moderate-resolution (30-metre) images, analysed by the European Commission's Joint Research Centre (Achard et al. 2004); and (3) numerous country- or region-level change analyses carried out by researchers from a variety of academic, governmental, and nongovernmental organizations. Two examples of NGO efforts are highlighted as case studies below.

Case Study 4.1: Forest Cover Change in Paraguay

Author: Ben White, Global Land Cover Facility (GLCF), University of Maryland
Indicator: tropical forest extent and change
Potential monitoring scales: landscape, small and large nations
Sensor: Landsat TM and Landsat Enhanced Thematic Mapper (ETM+)
Imagery cost/hectare: free

a. Introduction

The moist tropical forests, tropical grasslands, and savannas that make up the Atlantic Forest are one of the world's most diverse and endangered ecosystems. The forest has diminished to roughly 10 percent of its pre-Columbian extent, largely because of pressures from farming, logging, and population growth. Nevertheless, the remaining habitat is astonishingly diverse, with more than 2,000 estimated vertebrate species and more than 20,000 plant species.

By the early 1970s, the Brazilian interior Atlantic Forest was almost completely destroyed, while portions of the Atlantic Forest remained intact in Argentina and Paraguay. Although Brazil and Argentina established parks around Iguazú Falls to preserve portions of the forest, the majority of the Atlantic Forest in Paraguay has been almost entirely eliminated or fragmented. Today, the remaining Paraguayan Atlantic Forest is largely a function of accessibility and protected status.

Although circumstances leading to the post-1970 deforestation are complex, three significant regional dynamics are recognized. The construction of a dam at the northern tip of the Paraná River substantially impacted the watershed, which was tied to traditional land dynamics throughout most of Paraguay. The Central Bank of Paraguay and the Inter-American Development Bank (IADB) have determined that in recent years, there has also been an increasing lack of governance throughout the border departments (states), making environmental management increasingly challenging. Perhaps the most significant driver of land cover change was the introduction of mechanized soy agriculture. In Alta Paraná and Itapua departments, the correlation of deforestation with soy production was particularly strong.

b. Methods

The methodology for the Paraguayan forest cover change mapping was initiated with the coregistration of orthorectified Landsat TM with ETM+ Level1G imagery. A data mask was then developed, incorporating only those pixels that need to be classified. The masking was followed by a standard ISODATA clustering of the multitemporal Landsat imagery. A binary training mask was created for each class. The spectral clusters resulting from the ISODATA clustering were then labeled using an automated application developed by GLCF. The masking/labelling routine was repeated until all pixels were classified. As needed, the GLCF personnel performed any required editing and filtering. The classified tiles were then mosaicked into a single country product.

c. Results

The GLCF became involved with the Paraguayan conservation organization, Guyra Paraguay, in an effort to map the changing land cover and to help guide local, national, and NGO managers and stakeholders. GLCF staff was able to map the vegetation changes by using Landsat satellite imagery and the methods outlined above, while Guyra Paraguay provided the ground-truthing necessary to validate the GLCF results (figure 4.1). Since then, Guyra Paraguay has conducted its own updating of these deforestation

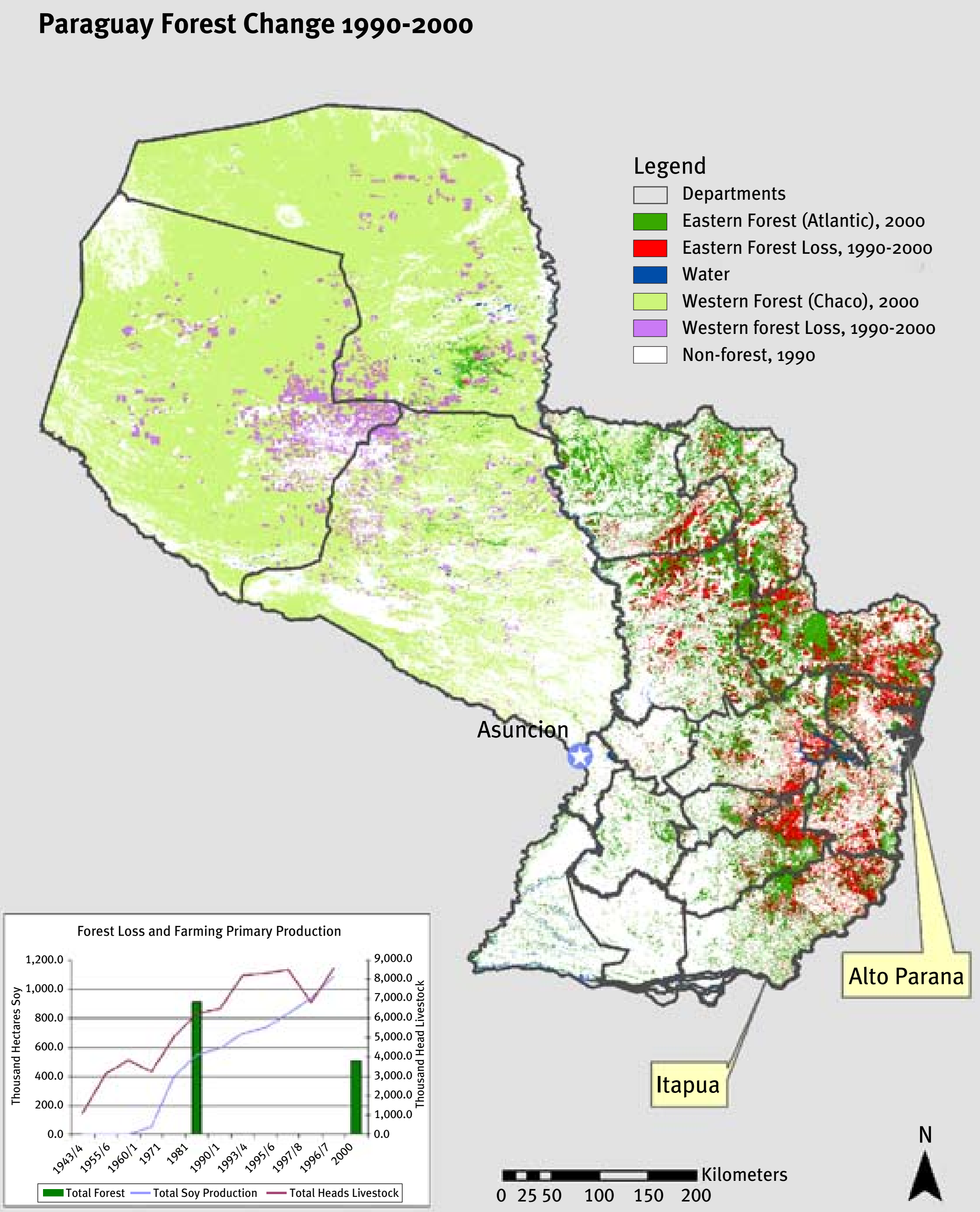


FIGURE 4.1 Forest change in Paraguay between 1990 and 2000.

maps, using MODIS data, and published the results in a national newspaper. This was used in a geographic information system (GIS) to create edge-area maps of each forest patch. The change over time in this ratio is reported per department. All of these data are available online at http://www.landcover.org.

Case Study 4.2: Dry Tropical Forest Mosaic of Eastern Cambodia

Author: Colby Loucks, World Wildlife Fund US (WWF)
Indicators: dry tropical forest extent
Potential monitoring scales: landscape, small and large nations
Sensor: Landsat TM and Landsat ETM+
Imagery cost/hectare: free
Limitations on accuracy: seasonality, fires, ground-truth data

a. Introduction

The dry forests of eastern Cambodia are the largest contiguous area of dry forest in all of mainland Southeast Asia. Cambodia's eastern plains are dominated by deciduous and dry dipterocarp forests, interspersed with patches of semievergreen forest. Many large mammal species require all three of these forest types to hunt or breed sometime during the year.

A study by the WWF produced an estimate of the distribution and change in extent from 1990 to 2002 of three types of forest: semievergreen, mixed deciduous, and dry dipterocarp. It estimated how much of each type was converted to agricultural, residential, or barren land cover.

b. Methods

The analysis was based on two Landsat images of the same area, both from the dry season: December 21, 1990, and February 13, 2002. WWF collected ground-reference data during surveys of the southeast portion of the study area. WWF also collected GIS data on topography, roads, villages, protected areas, and rivers to provide contextual information. These data were supplemented with interviews with local experts.

The analysis of the two images began with geometric registration of the 2002 image and then coregistration of the 1990 image to the 2002 image. This was achieved with subpixel accuracy (less than 30 metres). The two images, each with six data layers, one for each reflectance channel, were then combined to create a single two-date file with 12 data layers. This file was then used in an unsupervised classification to produce 250 classes, or clusters of data with greatest similarity among the 12 layers. These classes were then labeled (i.e., assigned to one of several possible cover types), referring to the suite of reference and supplemental data collected. Additional field surveys were conducted in areas where interpretation of the raw images was most difficult and where classification results were most suspect. The latter was evidenced by areas where several classes were interspersed in the results and where results appeared to conflict with experts notes. The data from the second survey were used to refine the initial classification. The final map was then filtered with a 3x3 grid cell box neighborhood focal filter. This filter returns the majority value to the centre pixel and filters out isolated pixels.

c. Results

Mapped results of the forest change analysis for Cambodia are presented in Figure 4.2. We found that 2.9% of the dry dipterocarp, mixed deciduous, and semi-evergreen forests in the study area were deforested over the 12 year time period (Table 4.1). The majority of the forest loss occurred near villages that existed in 1990. Expansion of these populated areas occurred over the 12 year period with the conversion of most of the forest to residential-agricultural lands. Additional forest loss was also found along road networks, several of which were created or improved since 1990. The semi-evergreen forests were deforested as a result of both conversion to swidden agriculture and deforestation along road networks that were built through these blocks of forests. We also found that 0.6% of the forests in the study area had regenerated (Table 4.1). The majority of the regeneration areas were from prior intensive timber operations. A small portion of the regenerating forest was from abandoned swidden agricultural lands found in semi-evergreen forests. Therefore we measured a net decrease in forest areas of 2.3% in the study area over the 12 year time frame. A majority of the study area still contains native land cover (89.1%), while approximately 9% of the study area has been converted to human-dominated land uses (i.e. residential or agricultural lands).

TABLE 4.1. Land cover classes and area for the land cover change analysis (1990-2002) in eastern Cambodia. Land cover classes are separated in static (non-change) classes and change classes. In the change classes, the text within the parenthesis indicates the general classes in 1990 and then in 2002.

Land Cover	Area (km2)	Percent of region of analysis
Semi-evergreen forest	94.4	12.0
Mixed deciduous forest (semi-dense)	186.3	23.7
Deciduous dipterocarp forest	409.5	52.2
Grasslands-scrub	6.3	0.8
Seasonal wetlands	3.4	0.4
Water	7.6	1.0
Seasonally bare land/Agricultural land	40.3	5.1
Residential-agricultural mosaic	9.2	1.2
Change Classes		
Deforested area (intact forest to bare land)	15.5	2.0
Degraded forest mosaic (intact forests to disturbed forests)	7.0	0.9
Regenerating forest mosaic (bare soil-agriculture to secondary forests)	3.8	0.5
Regenerating swidden agriculture (agriculture to secondary forests)	1.1	0.1
Water Expansion (agriculture to water)	0.8	0.1
Total	*785.3*	*100.0*

d. Limitations

As with many remote sensing analyses, knowledge of the region and forest types greatly increases the accuracy of the classification. This is especially the case with the dry deciduous forest mosaic found in eastern Cambodia. During the dry season, dry dipterocarp forests may resemble agricultural or seasonally bare areas in Landsat imagery. Burned agricultural lands may resemble naturally burned dry dipterocarp forests. Riparian forests resemble mixed deciduous or semievergreen forests, but are likely

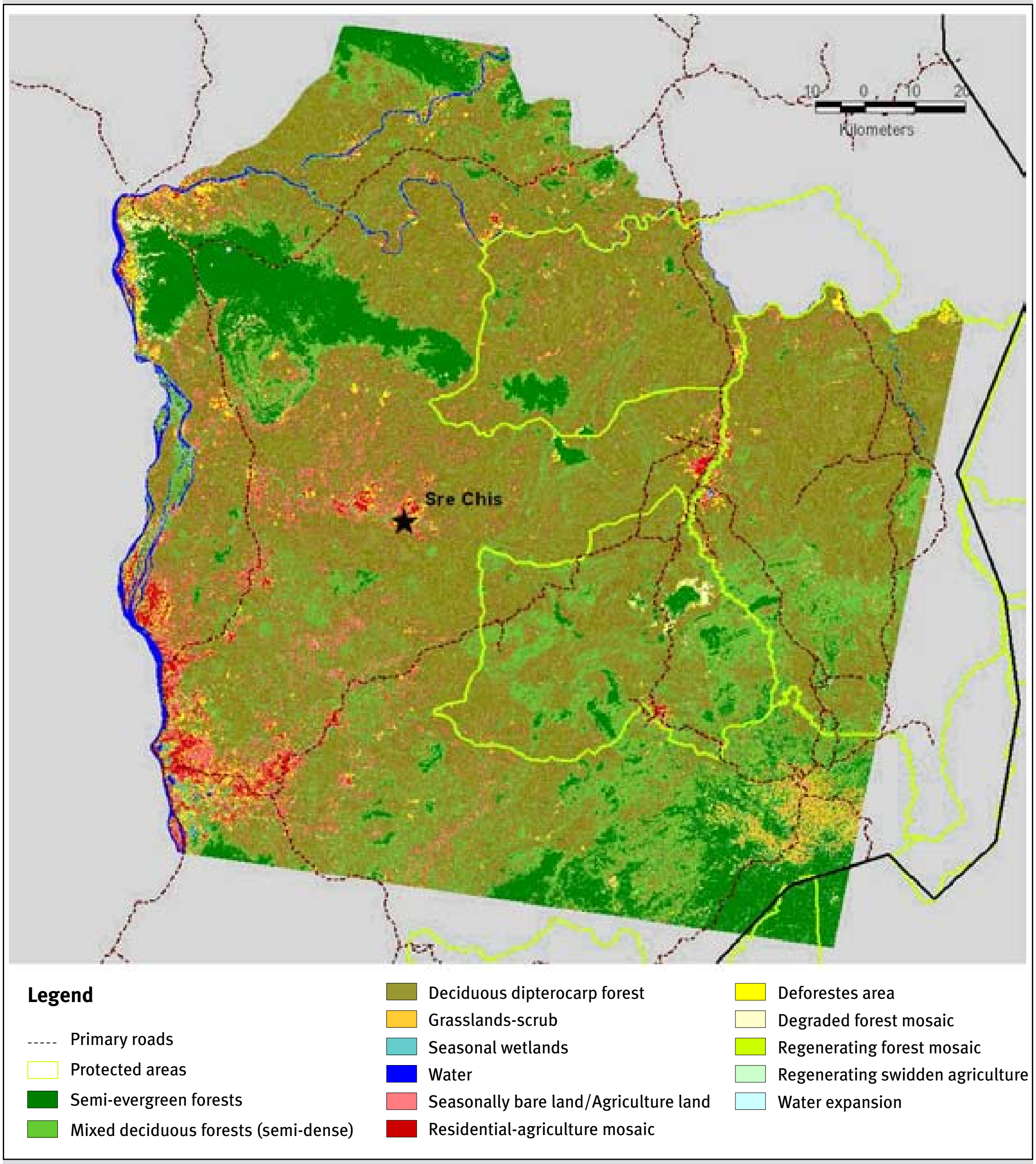


FIGURE 4.2 Final map of land cover change for the eastern Cambodia study area. “Deforested” and “regenerating” areas refer to changes in forest cover between 1990 and 2002.

important. Areas with perennial water supply are more likely to have semievergreen or mixed deciduous forests. The dry forest mosaic of eastern Cambodia is frequently burned, both by wildfires and by humans to stimulate growth of new plants. Burning frequency and extent confound land cover classification, with the potential to misclassify dry dipterocarp forests as "seasonally bare land." Recently burned land, whether it is an agricultural or natural area, has similar spectral signatures in the dry season. Firsthand knowledge of all these areas is likely to improve the final classification. The seasonality of this forest type argues for obtaining imagery for both the wet and dry seasons. Doing so will assist in classification by allowing comparison of seasonal signatures for each time period and determination of seasonality versus time-period changes in land cover. This also helps minimize misclassification among nonforest and dry forests.

Our initial supervised classification misrepresented the mixed deciduous forest class in the region. However, ground-reference data revealed an understory of bamboo. Thus, field verification was important for image interpretation and to accurately classify the mixed deciduous forest class. We also identified a number of areas in the semievergreen forests that were cleared for roads or small clearings that were misclassified as "mixed deciduous" or "dry dipterocarp" forests.

Because of the seasonal differences and proclivity of fires in dry tropical forests, spectral signatures differ considerably for the same habitat type. A constant challenge is to discern changes that are permanent, seasonal, or temporary. Most projects do not have funds for extensive field verification, especially in remote and inaccessible regions such as eastern Cambodia. However, local knowledge becomes of paramount importance for an accurate land cover classification.

4.2 Forest Quality

A number of forest indicators fall under the heading of forest quality, including (1) forest intactness, (2) large forest blocks, (3) forest fragmentation, (4) area and location of old growth, (5) area and location of plantations, (6) changes in forest pests and diseases, and (7) fire occurrence. Remote sensing has a role to play in assessing all of these indicators, and each will be briefly addressed below.

4.2.1 Forest intactness and large forest blocks

We know that natural forest landscapes lose components and functionality as human uses expand and continue over time. There exists a continuum of forest quality or "intactness," ranging from a totally pristine environment to a totally developed environment bereft of native species. Quantifiable and replicable indices and scales of measurement are needed to score forest landscapes on this continuum, and this is an active area for many conservation NGOs because of the importance of these forested areas to biodiversity. While methods have yet to be fully standardized, mapping of forest intactness continues to be carried out by a number of conservation organizations throughout the world. Monitoring forest intactness remains a conservation imperative and a valuable indicator for global and national forest monitoring.

An intact forest landscape does not necessarily consist of old trees and may not even be entirely forested. Simply stated, intact forest landscapes are contiguous mosaics of natural habitat types (forest and nonforest alike) in forest-dominated regions that either have never been subjected to industrial human activities or have sufficiently recovered from such activities in the past to the point where the composition, structure, and function of the forest landscape are relatively complete (Strittholt et al. 2006). In some localities (e.g., portions of Amazonia, Canada, Central Africa, Indonesia, Russia, and the United States), these are the remaining "frontier forests" as defined and mapped at a very coarse level by Bryant et al. (1997). In other localities, these are forest landscapes that have recovered from previous human disturbance to the point where they possess many, if not most, of their original forest characteristics (e.g., portions of the eastern United States and Canada, Eastern Europe, and portions of Asia). Also, it is important to note that intact forests are not static systems. On the contrary, an ecosystem with a high level of intactness is one that is able to maintain its biodiversity and ecosystem functionality over time—not in any fixed, quantitative sense, but rather as a dynamic property (O'Neill et al. 1986; Holling 1992).

To a large extent, many of the compositional (e.g., types of species present) and structural (e.g., size of trees and complexity of forest canopy) components of forest landscapes are size-independent. However, home range needs for some animal species and many ecological processes (e.g., natural regeneration, natural disturbance, nutrient cycling, predator-prey interactions, and migration and dispersal) require considerable areal extents to operate within their natural range of variability. Therefore, the definition of intact forest landscapes requires a reference to some minimum size. Natural disturbance regimes (e.g., fire, windthrow, and phase gap dynamics) and areal requirements of native, large home range species have been used repeatedly to help establish ecologically meaningful size thresholds for intactness.

To date, the Global Forest Watch (GFW) network, within the World Resources Institute, has advanced the mapping of intact forest landscapes more than any other organization. Using moderate resolution satellite remote sensing, GFW partners have mapped and continue to update forest intactness products for Brazil (Barreto et al. 2006), Canada (Smith et al. 2000; Lee et al. 2003; Lee et al. 2006), Central Africa (Minnemeyer 2002; Van de Pol et al. 2005), Chile (Neira et al. 2002), Indonesia (Achmaliadi et al. 2002), Russia (Yaroshenko 2001; Aksenov et al. 2002; Aksenov et al. 2006), the United States (Noguerón 2002; Strittholt et al. 2006), and Venezuela (Bevilacqua et al. 2002).

In 2002, GFW partners working in the boreal biome compiled existing forest intactness maps to form a panboreal map for the world (figure 4.3), and Greenpeace created a global forest intactness map based on standardized rules for mapping forest intactness thresholds (figure 4.4; Greenpeace 2006).

Based on a number of different remote sensing data sources, this study concluded that about 13 million square kilometres remain as intact forest landscapes (23 percent of the forest zone and 9 percent of the earth's surface). The remainder of the forest zone was identified as degraded, converted to plantations, or fragmented to areas smaller than 500 square kilometres in size by roads, settlements, etc. This global overview somewhat underestimates intactness because of the scale and definition of constraints, but it does provide a valuable global overview. The majority of the remaining intact forest landscapes of the world are located in the boreal/taiga forests of Alaska, Canada, and Russia (43.8 percent) and dense lowland tropical forests of the Amazon, Congo, and Southeast Asia Pacific (49 percent). The remaining intact forests are scattered widely among the other forest biomes. Of the intact forest landscapes, only 8 percent lie in strictly protected areas (IUCN categories I–III), according to the United Nations Environment Programme (UNEP)/IUCN World Database on Protected Areas (CBI unpublished report 2006). Of all countries full or partly within the forest zone, 82 (over half) have lost all of their intact forest landscapes. Of the remaining countries, half again have less than 10 percent of their forests still intact. Only 14 countries control more than 90 percent of the world's remaining intact forest landscapes, led by Canada, Brazil, Russia, Papua New Guinea, the Democratic Republic of the Congo, and Indonesia.

The monitoring of large forest blocks by country or by ecoregion is a valuable forest condition indicator that can be effectively achieved using moderate resolution remote sensing. These large blocks are important ecologically because they are the areas most likely to harbor native biodiversity and natural ecological and evolutionary function. With a monitoring process in place, these blocks can be tracked for change, and where they are being dissolved by human encroachment and use, we can anticipate negative ecological consequences. Monitoring forest intactness and large forest landscape blocks is a special subset of a more traditional national forest survey. Assessing intactness could be tied directly to national forest surveys or be handled separately.

- Intact forested area
- Intact non-forested area
- Fire disturbance area (includes human-induced fires)
- Non-intact forest landscape
- Forest outside the boreal (not studied)
- Rivers
- Lakes and oceans
- Selected cities and towns

FIGURE 4.3 Intact forest landscape mapping in the boreal forest biome (Unreviewed draft by Global Forest Watch, World Resources Institute).

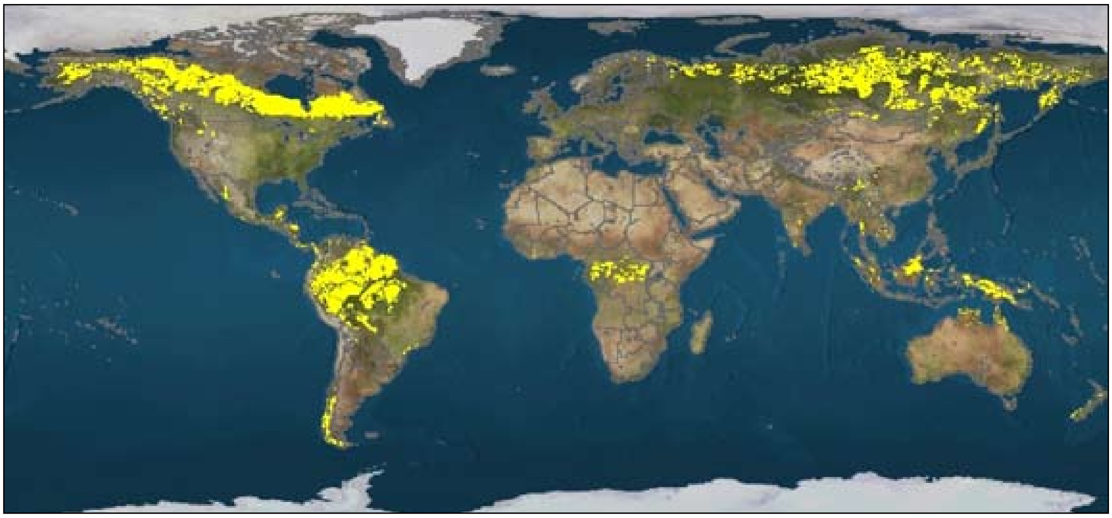


FIGURE 4.4 Intact forest landscapes (shown in yellow), as mapped by Greenpeace 2006.

4.2.2 Forest fragmentation

The destruction and fragmentation of natural habitats (including forests) is widely reported as the most significant driver in the global decline in biodiversity. Riitters et al. (2004) created digital forest fragmentation maps from GLCC land cover maps (AVHRR, circa 1992) where each pixel value represents a forest fragmentation category for the surrounding 81 square kilometre landscape. Repetition of this mapping assessment would provide a general global overview and highlight coarse spatial trends, but it will be unsuitable for addressing most biodiversity concerns resulting from forest fragmentation: ecological impacts on species operate at finer scales. Mapping forest fragmentation has been demonstrated using moderate-resolution imagery and ancillary data for entire countries such as the United States (Heilman et al. 2002; Riitters et al. 2002), which could be applied to other nations regardless of their size. (More in-depth discussion, including issues of data, metrics, standards, and scale in mapping fragmentation can be found in chapter 10.)

4.2.3 Area and location of old-growth forests

Because of the importance of old-growth forests to native biodiversity and its continuing decline, it is important in any global/national survey strategy to monitor where these forests exist and how they change over time. While still an area of active research for remote sensing, currently age (or area of old growth) in some forest community types can be mapped with moderate to high spatial and thematic accuracy. Most studies on mapping forest age (including old growth) have been conducted in temperate forest ecosystems, especially those dominated by conifers. For example, temperate rainforests have been successfully mapped based on moderate-resolution remote sensing data using a number of different analytical techniques. Cohen et al. (1995) used unsupervised classification to map discrete forest age classes in the U.S. Pacific Northwest and later mapped the same region modelling continuous age (Cohen et al. 2001). Ohmann and Gregory (2002) employed direct gradient analysis and nearest neighbor imputation to predict detailed site conditions. Jiang et al. (2004) mapped forest age in the same region, using a technique called "optimal iterative unsupervised classification," which resulted in accuracies between 80–90 percent for broadly defined age classes (figure 4.5). Old-growth forests also have been mapped for portions of the boreal forests of Russia (Aksenov et al. 1999), montane regions of tropical America (Costa Rica: Helmer et al. [2000]; Honduras: Aguilar [2005]), and oak-pine forests of western Mexico (Lammertink et al. 2007). In almost every case, ancillary data (e.g., slope, elevation, roads, and ownership) were employed to help interpret remote sensing signatures. In tropical forests, multitemporal remote sensing data has been shown to be necessary (Kimes et al. 1998). Using moderate resolution imagery is the most cost-effective method for mapping forest age over relatively large areas, but the next-generation sensors are pushing the level of spatial and thematic detail even more.

There is a growing body of knowledge about forest age, using high-resolution sensors such as IKONOS and airborne platforms (Franklin et al. 2001; Clark et al. 2003; Nelson et al. 2003). Although the various techniques mentioned here have proven to be feasible and reliable for mapping forest age, the future of mapping this important forest characteristic will be based on either active sensors (e.g., radar or lidar) alone (Drake et al. 2002) or through a combination of these sensors with moderate- (e.g., Landsat TM) or high-resolution (e.g., IKONOS) imagery (Lefsky et al. 2002).

There are always pros and cons to every forest survey decision. For some forest biomes, it is feasible in terms of quality of the results and cost today to map forest age with reasonable accuracy with moderate-resolution imagery at the national or subnational extent. In situations where fine resolution and very narrow age classes are required, more effort, additional data, and more cost are also required. From the global perspective, narrowing the scope of work to regions of particular interest or biological importance

FIGURE 4.5 Map of old (dark green) and mature (light green) conifer forests in the U.S. Pacific Northwest (Jiang et al. 2004).

over the near term is encouraged until technological advances and cost reductions are realized, allowing for more geographically broad application.

4.2.4 Area and location of plantations

Plantations continue to expand throughout the world, increasing by 2.8 million hectares per year during 2000–2005 (figure 4.6). According to the definitions used by the most recent global forest assessment by FAO (FRA 2005), plantations are defined as a subset of planted forests consisting primarily of exotic species. Plantation forests are further subdivided into two classes: forests planted for wood and fiber production (or productive plantations) and forests planted for protected soil and water (or protective plantations). Of the approximately 140 million hectares of plantations in the world (3.8 percent of all forest cover), 78 percent have been identified as productive plantations and 22 percent as protective plantations (FRA 2005). Plantations are generally of lesser biodiversity value than natural forests, especially when comprised of exotic species (Hunter 1999). Their expansion warrants monitoring, especially when they replace high-quality native forests.

Because of their commercial value, plantations have been the focus of many remote sensing studies, usually over small geographic extents and for purposes other than biodiversity. Remote sensing studies of plantations have focused predominantly on mapping plantation characteristics such as timber volume (Trotter et al. 1997), age (Jensen et al. 1999; Ratnayake 2006), and productivity (Coops et al. 1998). Fewer studies have addressed distinguishing plantations from native forests directly; nevertheless, some insights can be gleaned from these studies. Evans et al. (2002) mapped land cover change, with particular interest in mapping the conversion of native forests to plantations for a portion of the southeastern United States, using a combination of Landsat TM and aerial photographs. Donahey (2006) used multispectral images to map forest plantations in the Atlantic Forest region of Costa Rica. SPOT 4 imagery and Landsat TM were used to map vegetation changes in Central Sumatra with reasonable success in mapping plantation cover types (Trichon et al. 1999). All of these studies confirm the importance of integrating field data and usually a mixing of data from different sensors, including high resolution imagery.

The use of moderate resolution images (20–30 metres) alone usually proves inadequate, unless the plantations cover very large areas. The UNEP World Conservation Monitoring Centre (2007) has divided forest plantations into four classes (temperate/boreal exotic species plantation, temperate/boreal native species plantation, tropical exotic plantation, and tropical native plantation) and mapped them at a coarse scale, using AVHRR-based satellite images. This data set is too coarse to help address most biodiversity monitoring questions. Data at this scale will only identify major changes in forest cover, such as forest clearance.

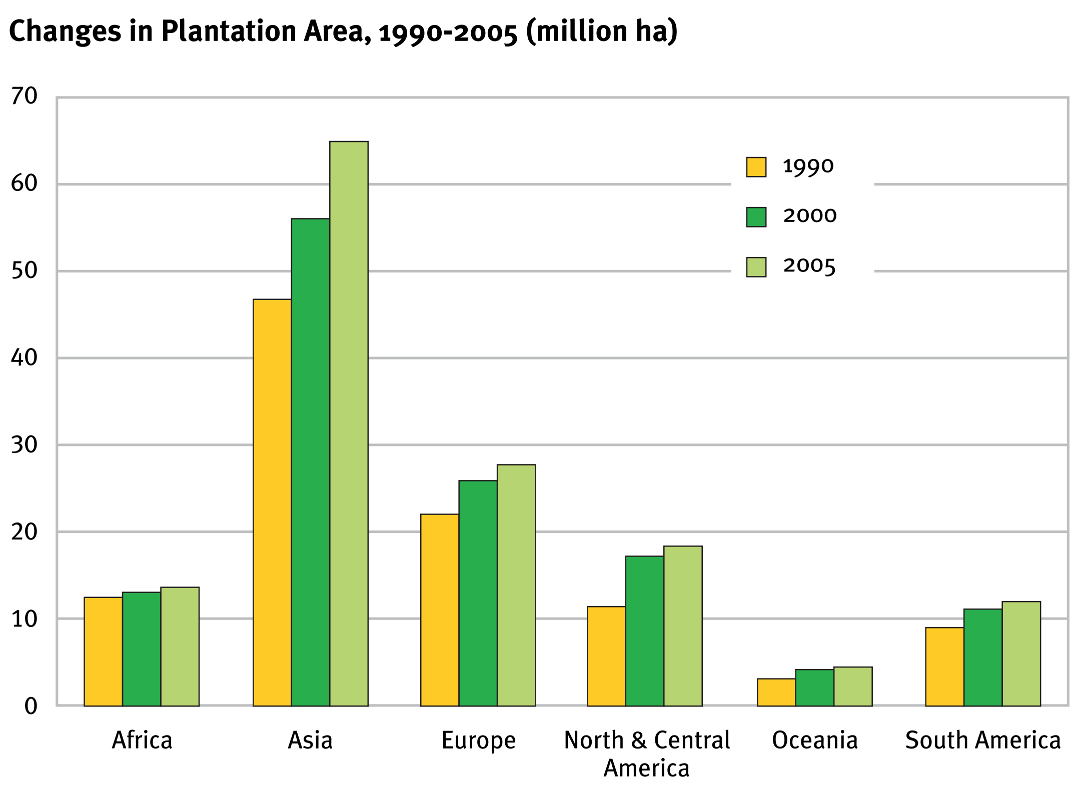


FIGURE 4.6 Changes in plantation area, 1990–2005 (FRA 2005).

In regions where plantation species are dramatically different from the native forest cover (e.g., conifers planted where deciduous forests are the natural forest), the detection and monitoring of plantation extent and spatial configuration are relatively straightforward, employing moderate- and high-resolution remote sensing. However, in regions where the planted tree species are similar to the native forest, the differentiation of plantations from natural forests is far more difficult (and nearly impossible in some cases) without the aid of ancillary data. Furthermore, all of the other regional constraints that affect forest mapping (e.g., persistent cloud cover) apply here as well.

4.2.5 Fire occurrence

Fire is the most common natural disturbance agent in forested ecoregions. Many forest species have evolved with fire, and some even require it for regeneration. Fires have a direct impact on local and regional biodiversity, which can be severely degraded under unnatural fire regimes. Poor forest management, human-caused ignitions, and (most important) climate change are fundamentally changing fire frequency, extent, and severity in many parts of the world. For that reason, monitoring forest fires is an extremely important indicator, and remote sensing provides an effective means for doing so (Fraser et al. 2000).

Satellite detection of fires now occurs in near-real time throughout much of the world (Tansey et al. 2004). Fires can be readily observed from optical satellite sensors. AVHRR (Fraser et al. 2000) and SPOT-

VEGETATION (Grégoire et al. 2003) have been used to map burnt areas. Ash from fires is dark in all three optical regions, and burn scars can be observed if the burn was severe and recent enough and if the canopy is open enough.

MODIS, deployed in 2000, currently dominates fire monitoring at both global and regional scales (Justice et al. 2002). Fire mapping derived from MODIS is available online with near-real-time mapping (http://maps.geog.umd.edu/firms/maps.asp). These products show a very large number of fire ignitions in equatorial Africa and South America, with the largest fires in the boreal zone. Monitoring at these scales provides extremely useful information regarding ecological processes such as carbon storage and nutrient budgets, which is important to biodiversity, but this scale of monitoring does not provide enough detail on the intensity and detailed spatial configuration of fires, which is also very important from the standpoint of biodiversity. For example, MODIS imagery can delineate a general fire perimeter, but closer examination with a higher-resolution sensor (e.g., Landsat TM) reveals the configuration and extent of various severities (figure 4.7). In this example, one can see areas of high severity (magenta) to areas untouched by the fire (green). There have been numerous studies integrating numerous sensors to understand the full impact of fires on natural systems (e.g., Steyaert et al. 1997).

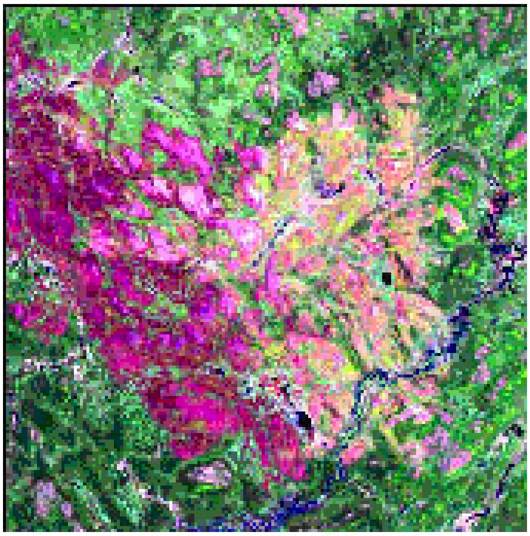


FIGURE 4.7 Landsat TM image showing a recent fire event in a boreal forest. Dark magenta depicts the highest-severity fire. Lighter shades of magenta, to pink, to yellow, and finally to green depict a decreasing level of fire severity. Note the spatial configuration of patches, which has a significant impact on the forest and its biodiversity. (Source: Conservation Biology Institute).

Tracking fire and its impacts is one aspect of forest-fire monitoring. Another is to assess changes in levels of fire susceptibility. From a societal perspective, this provides an early-warning system to mitigate property damage and loss of human life. From a biodiversity perspective, understanding where forest landscapes are becoming more susceptible to fire, especially if it is outside the range of natural variability for a given region, provides spatially explicit guidance as to where regional biodiversity will be at risk.

4.3 Threats

4.3.1 Deforestation

Systematic observations of the world's forests have been ongoing since the 1990s. From the standpoint of monitoring deforestation in the climate change equation, remote sensing is the only practical approach (DeFries et al. 2006). Since the 1990s, changes in forest extent based on coarse-and moderate resolution satellite imagery have been monitored reliably for climate change modelling. Coarse resolution sensors can detect only large-scale clearings, while clearings of 0.5 hectare can be detected in Landsat images with 30-metre resolution.

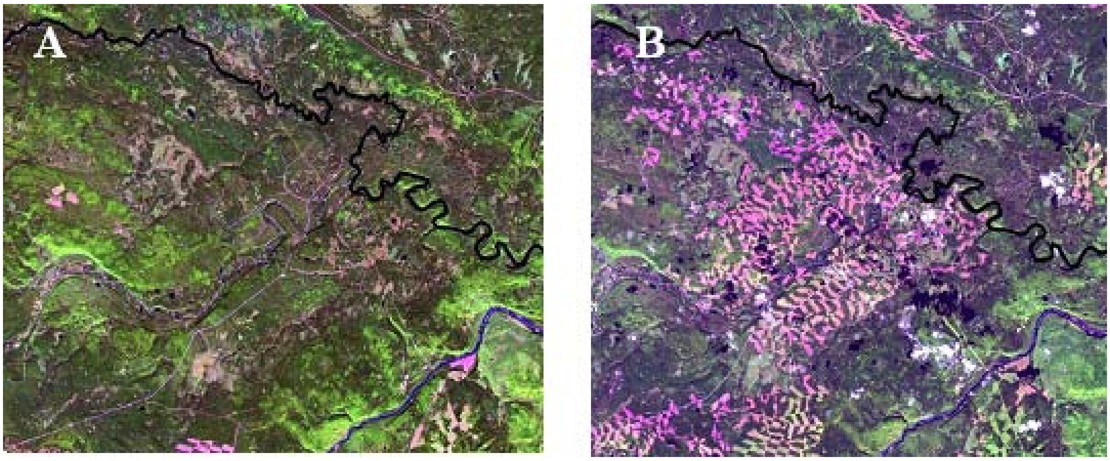


FIGURE 4.8 Landsat 5 images (A) 1990 and (B) 2000 for a portion of the boreal zone in Alberta, Canada, showing logging activity (magenta). (Courtesy of Global Forest Watch Canada).

Deforestation is not randomly distributed across the world (Tucker and Townsend 2000), so it is important to monitor some areas more intensely and at higher resolution, especially where there is high risk of occurrence. Sampling has been shown to be effective at estimating deforestation (Strahler et al. 2006). Therefore, the nonrandom nature of this human impact must be taken into account to develop an effective sampling strategy.

Figure 4.8 shows an example from Alberta, Canada where the impacts from clearcut forestry and oil and gas exploration have been dramatic over a 10-year period. More information on deforestation is contained in the discussion of ecosystem extent, especially in the case studies of Paraguay and Cambodia.

4.3.2 Invasive species

In many cases, it is possible to map the spread of, and impact from, specific invasive species (Van der Meer et al. 2002). There have been considerable advances in using remote sensing to map species that dominate forest canopies, including Surinam cherry or *Melaleuca quinquenervia* (McCormick 2002), tamarisk or *Tamarix chinensis* (Everitt and Deloach 1990), leucaena or *Leucaena leucocephala* (Tsai et al. 2005), maritime pine or *Pinus pinaster* (Ferreira et al. 2005), Chinese tallow or *Sapium sebiferum* (Ramsey et al. 2002), and trumpet tree (*Cecropia peltata*) (Lee et al. 1990).

The majority of plant invasives in native forests occur in the understory where they are often obscured by the canopy. However, where herbaceous weedy plants occur in forest openings and along forest edges and waterways, they are detectable. See, for example, leafy spurge or *Euphorbia esula* (Everitt et al. 1995), spotted knapweed or *Centaurea maculosa* (Lass et al. 2002), and cogongrass or *Imperata cylindrica* (Huang et al. 2001).

Silvicultural practices often enhance the effectiveness of invasives (Richardson 1998; Thysell and Carey 2001). Roads have been shown to be excellent conduits for alien species (Trombulak and Frissell 2000). Adjacent land uses, size of forest fragments, and amount of edge around forest fragments all affect invasion (With 2002). All of these can be monitored to varying degrees using remote sensing.

Another valuable use of remote sensing in monitoring invasive species is the effect that some invasives have on forest condition. Working in a Hawaiian montane rain forest, Asner and Vitousek (2005) used an airborne visible and infrared imaging spectrometer from an ER-2 high-altitude aircraft to measure water content and leaf nitrogen (N) concentrations in intact *Metrosideros polymorpha* forests and those invaded by *Myrica faya*, a nitrogen-fixing exotic tree, and *Hedychium gardnerianum*, an understory herb that reduces nitrogen concentration in forest canopies. Bonneau et al. (1999) used remote sensing to classify and track hemlock forests infested by the hemlock woolly adelgid, an exotic insect pest. Monitoring of invasive species is not exclusively a high-resolution endeavor. Bryceson (1991) tracked the Australian plague locust (*Chortoicetes terminiflora*) using Landsat TM imagery, and Kharuk et al. (2001) analysed large scale outbreaks of the Siberian moth (*Dendrolimus sibiricus*), using AVHRR imagery. (For more on invasive species, see chapter 11.)

4.3.3 Climate change – carbon storage and fire

Of all the identified drivers of forest biodiversity loss, climate change has the potential to become the leading agent in the coming decades, although its effects remain difficult to predict. Since 1900, the burning of fossil fuels has contributed the most to atmospheric greenhouse gases, although clearing and burning of tropical forests accounts for between 20 and 25 percent of anthropogenic greenhouse gases released each year (Moutinho and Schwartzman 2005). Forests act in concert with climate: influencing it while at the same time being influenced by it. When large areas are left undisturbed and forest growth exceeds harvest, forests can reduce carbon dioxide (CO_2) levels in the atmosphere and therefore are important to monitor at the global level. Unfortunately, the capacity of the world's forests to maintain native composition, structure, and function is being increasingly compromised by the multitude of the numerous stressors they face. With regard to climate-change modelling, remote sensing plays an important and effective role. It provides data on land cover, carbon stocks, rates of change, above-ground biomass, and even some human sources of methane (Rosenqvist et al. 2003).

Predictions concerning the types and severity of changes expected in forest ecosystem composition, structure, and function vary by forest biome and regional history (Watson et al. 1997). Most of the world's forests are expected to experience some level of disturbance caused by the changing climate, posing a serious threat to global forest biodiversity, forest-based economies, and ecosystem services. A growing body of scientific literature indicates that climate change is already affecting forests by shifting species ranges, fostering pests and pathogens, altering fire disturbance regimes, changing migration patterns, and causing species extinctions. Northern latitude and mountain forest systems are showing the greatest changes. Using time series AVHRR data (1981–1999), trends show a general increase in growing-season length, annual primary productivity, and northward extension of tree line in the Canadian boreal (Mynemi et al. 2001; Zhou et al. 2001). The Canadian boreal has also seen an increase in fire frequency and intensity over recent years (Gillett et al. 2004). In mountain forests, where native forests are also immediately vulnerable to climate change, species changes (including local extinctions) are being reported (Pounds et al. 1999). Monitoring forest ecosystems like tropical cloud forests will require integrating some of the newer remote sensing technologies (e.g., radar) with more-traditional sensors (e.g., Landsat or SPOT), but it could be done in a cost-effective manner because the geographic areas involved are relatively small.

Remote sensing has been shown to be effective at tracking carbon sequestration by forests in a timely and spatially explicit fashion over large regions (Dong et al. 2003), as well as small regions (Turner et al. 2004b), and mapping at both scales plays a substantial role in providing the necessary data for local-, regional-, and global-scale carbon cycle models (Turner et al. 2004a). Remote sensing provides an excellent opportunity to track this important forest function when used in connection with robust carbon mass balance models (Veroustraete and Verstraeten 2004). MODIS has been used frequently to monitor net primary productivity at global and regional scales (Liu et al. 1999), and historical Landsat imagery and JERS-1 SAR are the most useful sensors for establishing a 1990 carbon-stock baseline (Rosenqvist et al. 2003).

A variety of sensors have been used to map and monitor Central African land cover, including carbon sources and sinks (Laporte 2000). The biomass maps that are routinely updated (figure 4.9) provide insight into the changing landscape, which has direct impact on many forms of regional biodiversity. For example, this region is where Africa's great apes, including mountain gorillas (*Gorilla gorilla beringei*), lowland gorillas (*Gorilla gorilla gorilla)*, and bonobos (*Pan paniscus*) occur and where human-induced changes are resulting in rapid declines in many of the species. Monitoring biomass changes (carbon sources and sinks) not only supplies important monitoring data for ecological process models, which have the potential to predict biodiversity losses into the future, but it also provides important monitoring data that can be applied directly today to specific biodiversity concerns.

Forest fires are part of a feedback loop that relates to global climate change. When forests burn, they release carbon dioxide, thus adding to the greenhouse gases and raising the risk of future wildfires. In some parts of the world, where fire suppression has been effective, there has been forest-based fuel build-up. If more forests burn, whether from wildfires or increased prescribed burning, more carbon dioxide will be released back into the atmosphere, where it will join the increased emissions from human causes. Forest fires naturally release tons of carbon dioxide into the atmosphere each year. This is expected to increase in some regions, exacerbating climate change and with direct impacts on local and regional biodiversity. Therefore, mapping and monitoring forest fires are important activities for understanding the role that fires have in impacting climate change and biodiversity. As discussed earlier in this chapter, there is an extensive and ongoing monitoring effort of fires globally, using remote sensing.

4.3.4 Forest degradation

> *A degraded forest is a secondary forest that has lost, through human activities, the structure, function, species composition or productivity normally associated with a natural forest type expected on that site. Hence, a degraded forest delivers a reduced supply of goods and services from the given site and maintains only limited biological diversity. Biological diversity of degraded forests includes many non-tree components, which may dominate in the undercanopy vegetation.*
> — Ad hoc technical expert group on forest biological diversity, Convention on Biological Diversity (www.cbd.int/programmes/areas/forest/definitions.aspx).

Perhaps more than any other region in the world, the Amazon has been the focus of the most studies employing remote sensing to assess forest degradation, which in this region is dominated by selective logging and burning (Nepstad et al. 1999). Using a combination of 1-metre resolution IKONOS data and SPOT 4, Souza et al. (2003) developed a methodology that allowed them to map four classes of forest, including a degraded forest class, defined as either heavily burned or heavily logged and burned, using coarse imagery with accuracy of approximately 86 percent. Grainger (1999) focused on mapping the differences of biomass to map forest degradation.

Regardless of the main focus of mapping forest degradation, it is often important not only to adjust the monitoring frequency to fit the forest type—some forests require multiple surveys per year (e.g., dry tropical forests), while others require less frequent surveys (e.g., temperate coniferous forests)—but also to compile a long time series to differentiate natural variability from human degradation (Lambin 1999). Monitoring forest degradation in a standard way is an ongoing challenge. Remote sensing has been shown to be effective in tracking many characteristics of forests. What is missing are global and national standards for defining what forest degradation activities are most important to track in different regions and then developing a standard methodology so systematic monitoring can be carried out.

The implementation of remote sensing in forest monitoring will require a carefully designed strategy that takes advantage of a wide range of sensors, ancillary data, ground control, and local expertise. Once the data are in hand, it will also be important to find new ways to understand the many cumulative and synergistic threats to the world's forests so that meaningful solutions can be designed and implemented.

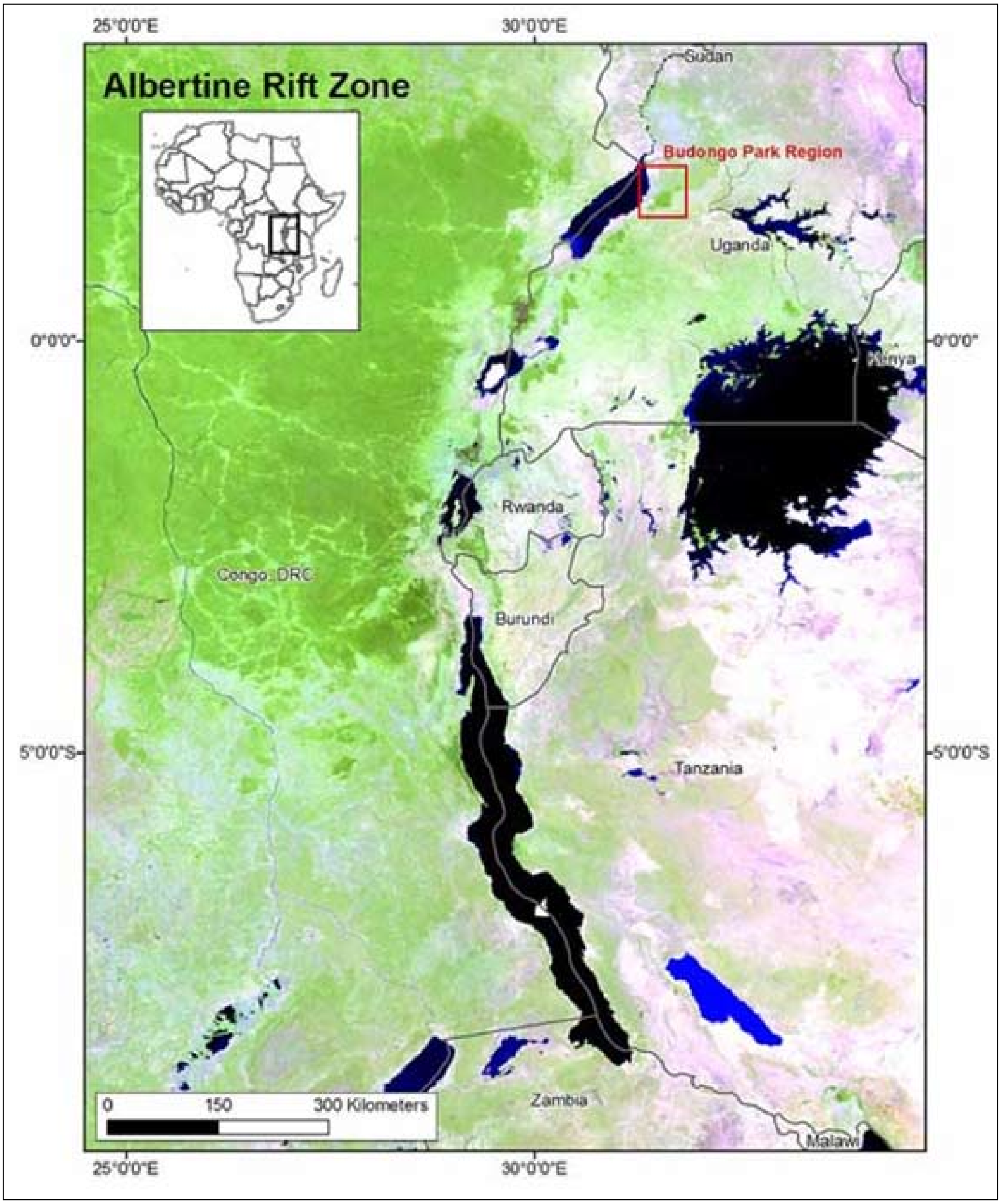


FIGURE 4.9 MODIS results showing biomass in Central Africa's Albertine Rift Zone (dark green = higher biomass, light green = lower biomass, and lavender = savannas). The red rectangle shows the Budongo Forest Reserve in southwest Uganda, where many of the surviving great apes are protected. Source: Laporte (2000).

4.4 Data and Other Resources

Global Forest Resources Assessment (FRA 2000 and FRA 2005)

The UN Food and Agricultural Organization, at the request of its member nations and the world community, has regularly reported on the state, changes, and conditions of the world's forests. The Global Forest Resources Assessment (FRA 2005) provides crucial information describing the state and conditions of forest resources for 2005 and as well as changes over the past 15 years. It is available on FAO's website along with past assessments.

The global forest map is one of the many outputs produced by these reports. The forest map in the 2000 report was produced from the Global Land Cover Characteristics Database (GLCCD), a land cover data set at 1-kilometre spatial resolution derived from AVHRR satellite images. In addition to a map showing the distribution of forests, maps of forests by ecological zones were also prepared. The forest map for the next assessment (FRA 2010) will be based on MODIS 250 m resolution data.

http://www.fao.org/forestry/en/

For forest maps see: www.fao.org/forestry/site/24815/en http://edcsns17.cr.usgs.gov/glcc/fao/index.html

FRA 2005: http://www.fao.org/forestry/site/fra2005/en/

Global Observation of Forest and Land Cover Dynamics

The stated objective of the Global Observation of Forest and Land Cover Dynamics (GOFC-GOLD) is to improve the quality and availability of observations of forests at regional and global scales and to produce useful, timely, and validated information products.

http://www.fao.org/gtos/gofc-gold/

Tropical Rain Forest Information Center

The Tropical Rain Forest Information Center was established to provide data, products, and information services to NASA. Landsat and other high resolution satellite remote sensing data, as well as digital deforestation maps and databases, are available online.

http://www.trfic.msu.edu/

Global Forest Watch

Global Forest Watch is an inititative of the World Resources Institute. It provides numerous forest maps (including atlases) and assessments online for various regions of the world, produced in collaboration with GFW partners in Brazil, Canada, Central Africa, Chile, Indonesia, Russia, Untited States and Venezuela.

http://www.globalforestwatch.org/english/index.htm

Global Fire Data

The University of Maryland provides historic and nearly real-time fire ignition data based on MODIS imagery at the global, regional, and national levels. Early-warning system details can be obtained from the Global Fire Monitoring Center (GFMC).

http://maps.geog.umd.edu/firms/maps.asp

http://www.gfmc.org/

Global Forest Fragmentation Data

Digital forest fragmentation maps derived from Global Land Cover Characterization (GLCC) land cover maps (based on Advanced Very High Resolution Radiometer AVHRR, circa 1992) are available online. Each pixel value represents a forest fragmentation category for the surrounding 81square kilometre landscape. The maps are directly comparable to the GLCC maps and are distributed by continent in the GLCC format.

http://www.srs.fs.usda.gov/4803/landscapes/global-index.html

National and Regional Forest Data Resources

Brazilian Amazon

Tropical Rain Forest Information Center provides numerous maps in pdf format for the region, including deforestation, forest cover, and forest classification.

http://www.trfic.msu.edu/products/amazon_products/amazonmaps.html

Amazon Forest Inventory Network (RAINFOR) is an international network established to monitor the biomass and dynamics of Amazonian forests.

http://www.geog.leeds.ac.uk/projects/rainfor/

Canada

Natural Resources Canada (NRCAN) provides numerous national forest themes and images.

http://www.nrcan.gc.ca/inter/products_e.html#data

Central Africa

Global Land Cover Facility provides forest change data for central Africa.

http://glcf.umiacs.umd.edu/data/amazonafrica/

Global Forest Watch provides forest assessment and atlas data for central Africa, particularly in Cameroon.

http://www.globalforestwatch.org/english/interactive.maps/cameroon.htm

Central America Land Cover

Center for International Earth Science Information Network (CIESIN) is a centre within the Earth Institute at Columbia University in the United States. CIESIN provides recent Central American land cover data online.

http://www.ciesin.columbia.edu/

SERVIR is a regional visualization and monitoring system for Mesoamerica that integrates satellite and other geospatial data and makes them widely available.

http://servir.nsstc.nasa.gov/lcluc/index.html

Europe

European Forest Institute is an independent nongovernmental organization conducting European forest research and providing numerous forest data layers for Europe.

http://dataservice.eea.europa.eu/dataservice/provider.asp?id=1B7DF740-552B-4BFE-97F1-6FFC3B8482A2

European Forest Information Scenario Model (EFISCEN) collects and provides national forest inventory data for 30 European nations, plus parts of Russia.

http://www.efi.int/projects/efiscen

India

Forest Survey of India assesses forest cover of the country on a two-year cycle, using satellite data. The main objectives are to present the information on Indian forest resources at state and district levels and to prepare forest cover maps on a 1:50,000 scale.

http://www.fsiorg.net/forestcovermap.htm

Southeast Asia

Tropical Rain Forest Information Center (TFRIC) provides numerous maps in pdf format for the region, including deforestation, forest cover, and forest classification.

http://www.trfic.msu.edu/products/seasia_products/seasiamaps.html

4.5 References

Achard, F., H. D. Eva, P. Mayaux, H.-J. Stibig, and A. Belward. 2004. Improved estimates of net carbon emissions from land cover change in the tropics for the 1990s. Global Biogeochemical Cycles 18: ART 91804.

Achmaliadi, R., I.G. Maha Adi, Y.M. Hardiono, H. Kartodihardjo, F.C.H. Malley, D.A. Mampioper, E.G.T. Manurung, A. Nababan, L.B. Pangkali, A. Ruwindrijarto, L.L.M. Situmorang, and Wardiyono. 2002. The state of the forest: Indonesia. Global Forest Watch. Washington, D.C. www.globalforestwatch.org/english/about/publications.htm. (accessed January, 2007).

Aguilar, A. 2005. Remote sensing of forest regeneration in highland tropical forests. GIScience and Remote Sensing 42(1): 66-79.

Aksenov, D., M. Karpachevskiy, S. Lloyd, and A. Yaroshenko. 1999. The last of the last: The old-growth forests of boreal Europe. Taiga Rescue Network. www.globalforestwatch.org/english/about/publications.htm. (accessed January, 2007).

Aksenov, D., et al. 2002. Atlas of Russia's intact forest landscapes. Global Forest Watch, World Resources Institute. Moscow, Russia. www.globalforestwatch.org/english/about/publications.htm. (accessed January, 2007).

Aksenov, D., M. Yu. Dubinin, M.L. Karpachevskiy, N.S. Liksakova, V.E. Skvortsov, D. Yu. Smirnov, and T.O. Yanitskaya. 2006. Mapping high conservation value forests of Primorsky Kray, Russian Far East. Global Forest Watch Russia. www.globalforestwatch.org/english/about/publications.htm. (accessed January, 2007).

Anger, C.D., S. Mah, and S.K. Babey. 1994. Technological enhancements to the compact airborne spectrographic imager (casi). Proceedings of the First International Airborne Remote Sensing Conference and Exhibition. Ann Arbor, Michigan: Environmental Research Institute of Michigan. 2: 205-213.

Asner, G.P., and P.M. Vitousek. 2005. Remote analysis of biological invasion and biogeochemical change. Ecology 102(12): 4383-4386.

Barreto, P., C. Souza Jr., R. Noguerón, A. Anderson, and R. Salomão. 2006. Human pressure on the Brazilian amazon forests. Amazon Institute of People and the Environment and World Resources Institute 2006. Washington, D.C. www.globalforestwatch.org/english/about/publications.htm. (accessed January, 2007).

Bartholomé, E., and A.S. Belward. 2005. GLC2000: A new approach to global land cover mapping from Earth observation data. International Journal of Remote Sensing 26(9): 1959-1977.

Bevilacqua, M., Cárdenas, L., Flores, A.L., Hernández, L., Lares B., E., Mansutti R., A., Miranda, M., Ochoa G., J., Rodríguez, M. and E. Selig. 2002.The State of Venezuela's Forests. A Case Study of the Guayana Region. A Global Forest Watch Report, World Resources Institute, Washington D.C., 132 pages.

Bonneau, L.R., K.S. Shields, and D.L. Civco. 1999. Using satellite images to classify and analyse the health of hemlock forests infested by the hemlock woolly adelgid. Biological Invasions 1:55-267.

Bryant, D., D. Nielsen, and L. Tangley. 1997. The last frontier forests: Ecosystems and economies on the edge. World Resources Institute. Washington, D.C.

Bryceson, K.P. 1991. Likely locust infestation areas in western New South Wales, Australia, located by satellite. Geocarto International 6(4): 21-37.

Clark, D.B., J.M. Read, M.L. Clark, A.M. Cruz, M.F. Dotti, and D.A. Clark. 2003. Application of 1-m and 4-m resolution satellite data to ecological studies of tropical rain forests. Ecological Applications 14(1): 61-74.

Cohen, W.B., Spies, T.A., and M. Fiorella. 1995. Estimating the age and structure of forests in a multi-ownership landscape of western Oregon U.S.A. International Journal of Remote Sensing 16(4): 721-746.

Cohen, W.B., T.K. Maiersperger, T.A. Spies, and D.R. Oetter. 2001. Modelling forest cover attributes as continuous variables in a regional context with Thematic Mapper data. International Journal of Remote Sensing 22: 2279-2310.

Coops, N.C., R.H. Waring, and J.J. Landsberg. 1998. Assessing forest productivity in Australia and New Zealand using a physiologically-based model driven with averaged monthly weather data and satellite-derived estimates of canopy photosynthetic capacity. Forest Ecology and Management 104: 113-127.

DeFries, R., F. Achard, S. Brown, M. Herold, D. Murdiyarso, B. Schlamadinger, and C. de Souza Jr. 2006. Reducing greenhouse gas emissions from deforestation in developing countires: Considerations for monitoring and measuring. GOFC-GOLD Rome, Italy.

Donahey, J. GIS and remote sensing analyses of forest plantations in Costa Rica's Atlantic Lowland Area. www.nrem.iastate.edu/ECOS/weblogs/Donahey_FinalReport2006.pdf. (accessed January, 2007).

Dong, J., R.K. Kaufmann, R.B. Myneni, C.J. Tucker, P.E. Kauppi, J. Liski, W. Buermann, V. Alexeyev, and M.K. Hughes 2003. Remote sensing estimates of boreal and temperate forest woody biomass: Carbon pools, sources, and sinks, Remote Sensing of Environment 84: 393-410.

Drake, J.B., R.O. Dubayah, D.B. Clark, R.G. Knox, J.B. Blair, M.A. Hofton, R.L. Chazdon, J.F. Weishampel, and S.D. Prince. 2002. Estimation of tropical forest structural characteristics using large-footprint lidar. Remote Sensing of Environment 79: 305-319.

Evans, J., N. Pelkey, and D. Haskell. 2002. An assessment of forest change on the Cumberland Plateau in Southern Tennessee. Report to the US EPA and USF&WS. lal.sewanee.edu/research/saa/index.html. (accessed January, 2007).

Everitt, J.H., and C.J. Deloach. 1990. Remote sensing of Chinese tamarisk (Tamarix chinensis) and associated vegetation. Weed Science 38(3): 273-278.

Everitt, J.H., G.L. Anderson, D.E. Escobar, M.R. Davis, N.R. Spencer, and R.J. Andrascik. 1995. Use of remote sensing for detecting and mapping leafy spurge (Euphorbia esula). Weed Technology 9(3): 599-609.

FAO (Food and Agriculture Organization). 2006. Expert Consultation on global forest resources assessment: towards FRA 2010: Kotka V. Kotka, Finland. www.metla.fi/tapahtumat/2006/kotkav/index.htm.

Ferreira, M.T., F.C. Aguiar, and C. Nogueira. 2005. Changes in riparian woods over space and time: Influence of environment and land use. Forest Ecology and Management 212: 145-159.

FRA 2000 . Global Forest Resources Assessment 2000: Main Report. Food and Agrilculture Organization. Rome, Italy. www.fao.org/forestry /site/fra2000report/en/.

FRA 2005. Global Forest Resources Assessment 2005: Progress towards sustainable forest management. Food and Agriculture Organization. Rome, Italy. www.fao.org/docrep/008/a0400e/a0400e00.htm. (accessed January, 2007).

Franklin, S.E., M.A. Wulder, and G.R. Gerylo. 2001. Texture analysis of IKONOS panchromatic imagery for Douglas-fir forest age class separability in British Columbia. International Journal of Remote Sensing 22: 2627-2632.

Fraser, R.H., Z. Li, and J. Cihlar. 2000. Hotspot and NDVI differnecing synergy (HANDS): A new technique for burned area mapping over boreal forest. Remote Sensing of Environment 74: 362-376.

Friedl, M.A., D.K. McIver, J.C.F. Hodges, X.Y. Zhang, D. Muchoney, A.H. Strahler, C.E. Woodcock, S. Gopal, A. Schneider, A. Cooper, A. Baccini, F. Gao, and C. Schaaf. 2002. Global land cover mapping from MODIS: Algorithms and early results. Remote Sensing of Environment 83(1-2): 287-302.

Friedl, M.A. 2007. Validation of the consistent-year v003 MODIS land cover product. www-modis.bu.edu/landcover/userguidelc/consistent.htm. (accessed January, 2007).

Gillett, N.P., Weaver, A.J., Zwiers, F.W. and M.D. Flannagan. 2004. Detecting the effect of human-induced climate change on Canadian forest fires. Geophysical Research Letters 31 (18): L18211.

GOFC-GOLD. 2004. CEOS land cover validation workshop. Boston, MA. 2-5 February 2004.

Grainger, A. 1999. Constraints on modelling the deforestation and degradation of tropical open woodlands. Global Ecology and Biogeography 8(3-4): 179-190.

Greenpeace. 2006. Roadmap to recovery: The world's last Intact forest landscapes. www.intactforests.org/publications/publications.htm. (accessed January, 2007).

Grégoire, J., K. Tansey, and J. Silva. 2003. The GBA2000 initiative: Developing a global burnt area database from SPOT-VEGETATION imagery. International Journal of Remote Sensing 24(6): 1369-1376.

Hansen, M., R.S. DeFries, J.R.G. Townshend, M. Carroll, C. Dimiceli, and R.A. Sohlberg. 2003. Global percent tree cover at a spatial resolution of 500 meters: First results of the MODIS vegetation continuous fields algorithm."Earth Interactions 7(10): 1-15.

Hansen, M., and R. DeFries. 2004. Detecting long term forest change using continuous fields of tree cover maps from 8km AVHRR data for the Years 1982–99. Ecosystems 7: 695–716.

Heilman, Jr. G.E., J.R. Strittholt, N.C. Slosser, and D.A. DellaSala. 2002. Forest fragmentation of the conterminous United States: Assessing forest intactness through road density and spatial characteristics. Bioscience 52(5): 411-422.

Helmer, E.H., S. Brown, and W.B. Cohen. 2000. Mapping montane tropical forest successional stage and land use with multi-date Landsat imagery. International Journal of Remote Sensing 21(11): 2163-2183.

Holling, C.S. 1992. Cross-scale morphology, geometry, and dynamics of ecosystems. Ecological Monographs 62:447-502.

Huang, Y., M. Bruce, L. Byrd, and J. Mask. 2001. Using wavelet transform of hyperspectral reflectance curves for automated monitoring of Imperata cylindrical (cogongrass). GEOScience and Remote Sensing 5: 2244-2246.

Hunter, M.L. 1999. Maintaining Biodiversity in Forest Ecosystems. Cambridge University Press. New York NY., 1999.

Jensen, J.R., F. Qiu, and M. Ji. 1999. Predictive modelling of coniferous forest age using statistical artificial neural network approaches applied to remote sensor data. International Journal of Remote Sensing 20(14): 2805-2822.

Jiang, H., J.R. Strittholt, P.A. Frost, and N.C. Slosser. 2004. The classification of late seral forests in the Pacific Northwest, USA using Landsat ETM+ imagery. Remote Sensing of Environment 91: 320-331.

Justice, C.O., L. Giglio, S. Korontzi, J. Owens, J.T. Morisette, D. Roy, J. Descloitres, S. Alleaume, F. Petitcolin, and Y. Kaufman. 2002. The MODIS fire products. Remote Sensing and Environment 83: 244-262.

Kerr, J.T., and M. Ostrovsky. 2003. From space to species: Ecological applications for remote sensing. Trends in Ecology and Evolution 18(6): 299-314.

Kharuk, V.I., A.A. Kozhukhovskaya, I.A. Pestunov, K. Ranson, and G.M. Tsibul'skiy. 2001. Use of NOAA/AVHRR imagery in monitoring Siberian moth outbreaks. Mapping Sciences and Remote Sensing 38(4): 272-281.

Kimes, D.S., R.F. Nelson, D.L. Skole, and W.A. Salas. 1998. Accuracies in mapping secondary tropical forest age from sequential satellite imagery. Remote Sensing and Environment 65(1): 112-120.

Lambin, E.F. 1999. Monitoring forest degradation in tropical regions by remote sensing: some methodological issues. Global Ecology and Biogeography 8(3-4): 191-198.

Lammertink, J.M., J.A. Rojas-Tome, F.M. Casillas-Orona, and R.L. Otto. 2007. Estatus y conservación de los bosques maduris y la saves endémicas en la zona de pino-encino de la Sierra Madre Occidental, México. www.worldwildlife.org/bsp/publications/lac/status/status1.html#methods. (accessed January, 2007).

Laporte, N. 2000. An integrated forest monitoring system for Central Africa. lcluc.umd.edu/products/pdfs/GOFC/GOFC-LaPorte2000.pdf. (accessed January, 2007).

Lass, L.W., D.C. Thill, B. Shafii, and T.S. Prather. 2002. Detecting spotted knapweed (Centaurea maculosa) with hyperspectral remote sensing technology. Weed Technology 16(2): 426-432.

Lee, D.W., R.A. Bone, S.L. Tarsis, and D. Storch. 1990. Correlates of leaf optical properties in tropical forest sun and extreme-shade plants. American Journal of Botany 77(3): 370-380.

Lee, P., D. Aksenov, L. Laestadius, R. Noguerón, and W. Smith. 2003. Canada's large intact forest landscapes. Global Forest Watch Canada and World Resources Institute. Washington, DC. www.globalforestwatch.org/english/about/publications.htm. (accessed January, 2007).

Lee, P., J.D. Gysbers, and Z. Stanojevic. 2006. Canada's forest landscape fragments: A first approximation. Global Forest Watch Canada. Edmonton, Alberta. 2006. www.globalforestwatch.ca/publications_and_maps.htm. (accessed January, 2007).

Lefsky, M.A., W.B. Cohen, G.G. Parker, and D.J. Harding. 2002. Lidar remote sensing for ecosystem studies. Bioscience 52(1): 19-30.

Liu, J., J.M. Chen, J. Cihlar, and W. Chen. 1999. "Net primary productivity distribution in the BOREAS region from a process model using satellite and surface data." Journal of Geophysical Research 104.D22: 27735-27754.

Loveland, T.R., B.C. Reed, J.F. Brown, D.O. Ohlen, J. Zhu, L.Yang, and J.W. Merchant. 2000. Development of a global land cover characteristics database and IGBP DISCover from 1-km AVHRR data. International Journal of Remote Sensing 21(6/7): 1303-1330.

Mayaux, P., and E.F. Lambin. 1997. Tropical forest area measured from global land-cover classification: Inverse calibration models based on spatial textures. Remote Sensing of Environment 59: 29-43.

Mayaux, P., A. Strahler, H. Eva, M. Herold, A. Shefali, S. Naumov, S. Dorado, C. Di Bella, D. Johansson, C. Ordoyne, I. Kopin, L. Boschetti, and A. Belward. 2006. Validation of the global land cover 2000 map. IEEE-Transactions on Geoscience and Remote Sensing 44(7): 1728-1739.

McCormick, C.M. 2002. Mapping exotic vegetation in the Everglades from large-scale aerial photographs. Photogrammetric Engineering and Remote Sensing 65(2): 179-184.

McIver, D.K., and M.A. Friedl. 2002. Using prior probabilities in decision-tree classification of remotely sensed data. Remote Sensing of Environment 81(2-3): 253-261.

Minnemeyer, S. 2002. An analysis of access into central Africa's rainforests. Global Forest Watch. Washington, DC. www.globalforestwatch.org/english/about/publications.htm. (accessed January, 2007).

Mollicone, D., F. H. Achard, A. Eva, S. Belward, A. Federici, V.C. Lumicisi, H. Risso, Stibig, and R. Valentini. 2003. Land use change monitoring in the framework of the UNFCCC and its Kyoto Protocl: Report on current capabilities of satellite remote sensing technology. European Communities, Luxembourg, 2003..

Moran, M.S., T.R. Clarke, Y. Inoue, and A. Vidal. 1994. Estimating crop water deficit using the relation between surface-air temperature and spectral vegetation index. Remote Sensing and Environment 49: 246-263.

Moutinho, P., and S. Schwartzman. 2005. Tropical deforestation and climate change. Amazon Institute of Environmental Research.

Myneni R.B., Dong J., Tucker C.J., Kaufmann R.K., Kauppi P.E., Liski J., Zhou L., Alexeyev V., and M.K. Hughes. 2001. A large carbon sink in the woody biomass of Northern forests. Proceedings of the National Academy of Sciences of the USA 98: 14784–14789.

Neira, E., H. Verscheure, and C. Revenga. 2002. Chile's frontier forests: Conserving a global treasure. Global Forest Watch,. Washington,D.C. www.globalforestwatch.org/english/about/publications.htm. (accessed January, 2007).

Nelson, T., K.O. Niemann, and M. Wulder. 2003. Spatial statistical techniques for aggregating point objects extracted from high spatial resolution remotely sensed imagery. Journal of Geographical Systems 4: 423-433.

Nepstad, D.C., J.A. Verissimo, A. Alencar, C. Nobre, E. Lima, P. Lefebvre, P. Schlesinger, C. Potter, P. Moutinho, E. Mendoza, M. Cochrane, and V. Brooks. 1999. Large-scale impoverishment of Amazonian forests by logging and fires. Nature 398: 505-508.

Noguerón, R. 2002. Low-access forests and their level of protection in North America. World Resources Institute. Washington, D.C. www.globalforestwatch.org/english/about/publications.htm. (accessed January, 2007).

Ohmann, J.L. and Gregory, M.J. 2002. Predictive mapping of forest composition and structure with direct gradient analysis and nearest-neighbor imputation in coastal Oregon, U.S.A. Canadian Journal of Forest Research 32: 725-741.

O'Neill, R.V., et al. 1986. A hierarchical concept of ecosystems. Princeton University Press.

Ramsey, E.W., G.A. Nelson, S.K. Sapkota, E.B. Seeger, and K.D. Martella. 2002. Mapping Chinese tallow with color-infrared photography. Photogrammetric Engineering and Remote Sensing 68(3): 251-255.

Ratnayake, R.L. 2006. Identification of age groups of managed pine plantation using remote sensing data. www.gisdevelopment.net/proceedings/mapindia/2006/envi.htm. (accessed January, 2007).

Richardson, D.M. 1998. Forestry trees as invasive species. Conservation Biology 12(1): 18-26.

Riitters, K., J. Wickham, R. O'Neill, B. Jones, E. Smith, J. Coulston, T. Wade, and J. Smith. 2002. Fragmentation of continental United States forests. Ecosystems 5(8): 815-822.

Riitters, K., J. Wickham, R. O'Neill, B. Jones, and E. Smith. 2004. Global-scale patterns of forest fragmentation. Conservation Ecology 4(2): 3. http://www.consecol.org/vol4/iss2/art3/.

Rosenqvist, A., A. Milne, R. Lucas, M. Imhoff, and C. Dobson. 2003. Environmental Science and Policy 6: 441-455.

Smith, W., B. Evans, T. Wilson, A. Nikiforuk, K. Baltggailis, A. Brady, L. Brewster, T Gray, W. Horter, P. Lee, R. Livernash, C. McGlynn, S. Minnemeyer, A. O'Carroll, A. Penn, G. Quaile, M. Sawyer, E. Selig, and D. Bryant. 2000. Canada's forests at a crossroads: An assessment in the year 2000. World Resources Institute, Washington, D.C.. www.globalforestwatch.org/english/about/publications.htm. (accessed January, 2007).

Souza, Jr. C., L. Firestone, L.M. Silva, and D. Roberts. 2003. Mapping forest degradation in the Eastern Amazon from SPOT4 through spectral mixture models. Remote Sensing of Environment 87: 494-506.

Strahler, A.H., L. Boschetti, G.M. Foody, M. Friedl, M. Hansen, M. Herold, P. Mayaux, J. Morisette, S. Stehman, and C.E. Woodcock. 2006. Global land cover validation: Recommendations for evaluation and accuracy assessment of global land cover maps. European Communities, Luxembourg.

Steininger, M.K. 1996. Tropical secondary forest regrowth in the Amazon: Age, area and change estimation with Thematic Mapper data. International Journal of Remote Sensing 17(1): 9-27.

Steininger, M.K., C.J. Tucker, J.R.G. Townshend, T.J. Killeen, A. Desch, V. Bell, and P. Ersts. 2001. Tropical deforestation in the Bolivian Amazon. Environmental Conservation 28: 127-134.

Steyaert, L.T., F.G. Hall, and T.R. Loveland. 1997. Land cover mapping, fire regeneration, and scaling studies in the Canadian boreal forest with 1km AVHRR and Landsat TM data. Journal of Geophysical Research 102.D24: 581-598.

Strittholt, J.R., R. Noguerón, M. Alvarez, and J. Bergquist. 2006. Mapping undisturbed landscapes in Alaska: An overview report. Conservation Biology Institute and World Resources Institute. www.globalforestwatch.org/english/about/publications.htm (accessed January, 2007).

Tansey, K., J-M. Grégoire, D. Stroppiana, A. Sousa, J.M.N. Silva, J.M.C. Pereira, L. Boschetti, M. Maggi, P.A. Brivio, R. Fraser, S. Flasse, D. Ershov, E. Binaghi, and D. Graetz. 2004. Vegetation burning in the year 2000: Global burned area estimates from SPOT VEGETATION data. Journal of Geophysical Research 109.D14: CiteID D14S03.

Thysell, D.R. and A.B. Carey. 2001. Manipulation of density of Psudotsuga menziesii canopies: preliminary effects on understory vegetation. Canadian Journal of Forest Research 31(9): 1513-1525.

Treuhaft, R.N., B.E. Law, and G.P. Asner. 2004. Forest attributes from radar interferometric structure and its fusion with optical remote sensing. Bioscience 54: 561-571.

Trichon, V., D. Ducrot, and J.P. Gastellu-Etchegorry. 1999. SPOT4 potential for the monitoring of tropical vegetation: A case study in Sumatra. International Journal of Remote Sensing 20(14): 2761-2785.

Trombulak, S.C. and C.A. Frissell. 2000. Review of ecological effects of roads on terrestrial and aquatic communities. Conservation Biology 14(1): 18-30.

Trotter, C.M., J.R. Dymond, and C.J. Goulding. 1997. Estimation of timber volume in a coniferous plantation forest using Landsat TM. International Journal of Remote Sensing 18(10): 2209-2223.

Tsai, F., E. Lin, and H. Wang. 2005. Detecting invasive plant species using hyperspectral satellite imagery. GEOScience and Remote Sensing Symposium, 2005, IGARSS'05 Proceedings. 2005 IEEE International 4:3002-3005.

Tucker, C. J., and J.R.G. Townshend. 2000. Strategies for tropical forest deforestation assessment using satellite data. International Journal of Remote Sensing, 21: 1461-1472.

Turner, D.P., S.V. Ollinger, and J.S. Kimball. 2004a. "Integrating remote sensing and ecosystem process models for landscape to regional scale analysis of the carbon cycle." Bioscience 54(6): 573-584.

Turner, D.P., M. Guzy, M.A. Lefsky, W.D. Ritts, S. van Tuyl, and B.E. Law. 2004b. "Monitoring forest carbon sequestration with remote sensing and carbon cycle modelling." Environmental Management 33(4): 457-466.

UNEP World Conservation Monitoring Centre. 2007. Global Distribution of Current Forests. http://www.unep-wcmc.org/forest/global_map.htm (accessed June 2007)

Van der Meer, F., Schmidt, K.S., Bakker, A., & Bijker, W., 2002. New Environmental RS systems. In: Environmental Modelling with GIS and RS. Skidmore, A. K., editor, Taylor & Francis, London, pp. 26-51.

Van de Pol, M.J., L.A. Nsoyuni, S. Minnemeyer, and R. Ngoufo. 2005. Interactive forestry atlas of Cameroon (version 1.0): An overview. Global Forest Watch. Washington, DC. www.globalforestwatch.org/english/about/publications.htm. (accessed January, 2007).

Veroustraete, F., and W.W. Verstraeten. 2004. European forest carbon mass balance estimated with remote sensing and the production efficiency model C-fix: A hot future unfolds for Kyoto Protocol implementation. American Geophysical Union, Fall Meeting 2004. adsabs.harvard.edu/abs/2004AGUFM.B43C.06V. (accessed January, 2007).

Watson, R.T., M.C. Zinyowera, R.H. Moss, and D. Dokken. 1997. IPCC special report on the regional impacts of climate change: An assessment of vulnerability. Intergovernmental Panel on Climate Change. www.grida.no/climate/ipcc/regional/198.htm. (accessed January, 2007).

With, K.A., Pavuk, D.M., Worchuck, J.L., Oates, R. K., Fisher, J.L. 2002. Threshold Effects of Landscape Structure on Biological Control in Agroecosystems. Ecological Applications 12 (1): 52-65.

Wulder, M.A., R.J. Hall, N.C. Coops, and S.E. Franklin. 2004. High spatial resolution remotely sensed data for ecosystem characterization. Bioscience 54(6): 511-521.

Yaroshenko, A. 2001. The last intact forest landscapes of Northern European Russia. Greenpeace Russia and Global Forest Watch.

Zhou, L., C.J. Tucker, R.K. Kaufmann, D. Slayback, N.V. Shabanov, I. Fung, and R.B. Myneni. 2001. "Variations in northern vegetation activity inferred from satellite data and vegetation index during 1981-1999." Journal of Geophysical Research 106: 20069-20083.

Chapter 5. Trends in Selected Biomes, Habitats, and Ecosystems: Dry and Sub-humid Lands

AUTHORS: Holly Strand[1], Peter Leimgruber[2], Thomas Mueller[2]
CONTRIBUTORS: Jessica Forest[3], Eric Sanderson[3], Peter Coppolillo[3], Guy Picton Phillipps[3] and G. Gray Tappan[4]
REVIEWERS: Jaime Webbe[5], Michael A. White[6]

1 World Wildlife Fund (WWF-US) and Utah State University, 2 Smithsonian National Zoological Park, 3 Wildlife Conservation Society, 4 SAIC EROS Data Center, 5 Secretariat of the Convention on Biological Diversity, 6 Utah State University

Remote sensing based indicators for dry and sub-humid lands:

- Extent of grassland, desert and Mediterranean ecosystems
- Intact biodiversity
- Land degradation
- Grazing pressure
- Extent of alien species invasion
- Climate change
- Fire location and frequency

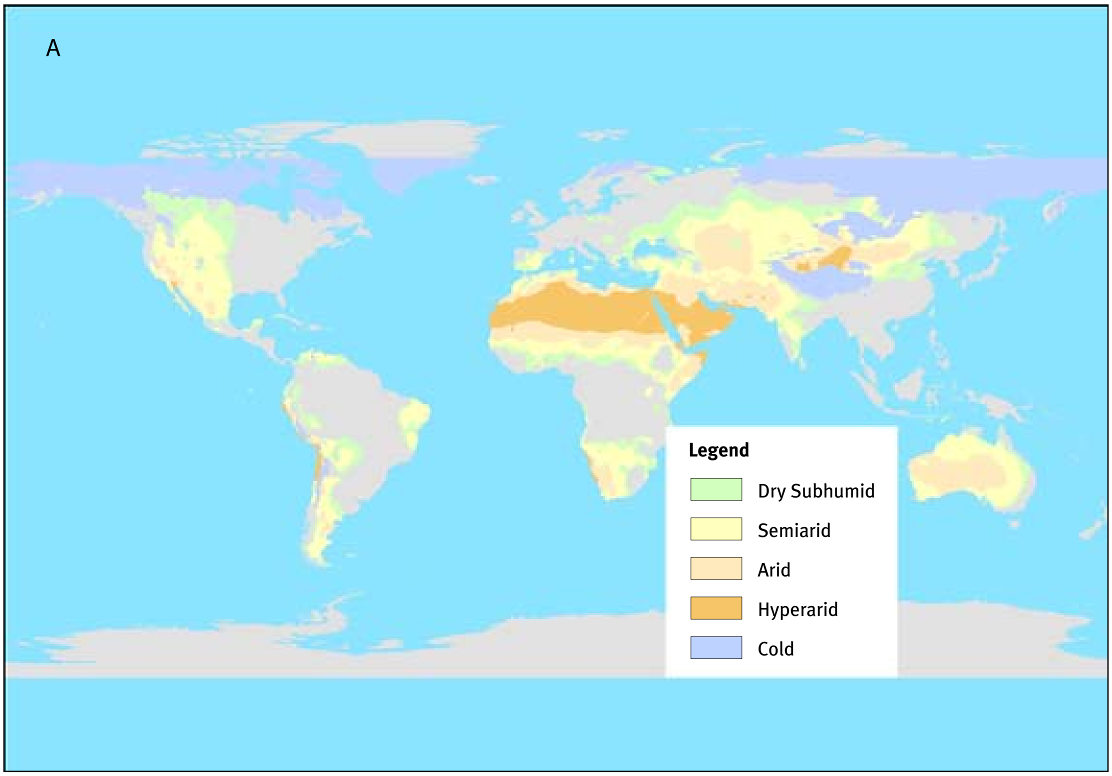
Remote sensing has been used with varying degrees of success when considering biodiversity indicators in dry and sub-humid lands. Changes in biodiversity are most often represented as habitat or ecosystem conversion (change in extent); changes in habitat or ecosystem quality, including ecological processes; and occurrence and distribution of threats to biodiversity.

5.1 Delineating Cover and Estimating Change in Extent

A single definition for the delineation of dry and sub-humid lands within a monitoring context has yet to be determined. Part I, Article 1 of the United Nations Convention to Combat Desertification refers to arid and sub-humid lands as areas, other than polar, subpolar, and hyperarid regions, with a ratio of annual precipitation to potential evapotranspiration under 0.65 (UNCCD 1994**;** Middleton and Thomas 1992). Meanwhile, land cover types measurable by remote sensing correspond more closely to an ecosystem-based definition of dry and sub-humid lands as per the definition adopted by the Convention on Biological Diversity. They include Mediterranean landscapes, grasslands and savannas, and deserts. Figures 5.1a and 5.1b compare the distribution of UNCCD aridity zones with an example of dryland cover types identified by remote sensing. For more information on definition issues for the CBD and UNCCD, see Sörensen (2007).

Other criteria for delineating and categorizing dryland ecosystems include tree cover thresholds (Intergovernmental Panel on Climate Change 2004; Scholes and Hall 1996), vegetation height (for example, Bartholomé and Belward 2005), vertical vegetation complexity (that is, numbers of canopy strata [Scholes and Hall 1996]), disturbance regime (fire or drought [White et al. 2000]), and land use (for example, rangeland and grazing systems [McNaughton 1985, 1993]). Some definitions use these factors in combination. Remote sensing has been used to characterize all of these with some degree of accuracy. As with forests, sensors such as VEGETATION, MODIS, and AVHRR that sample the Earth's surface frequently are useful for distinguishing general patterns of distribution; TM, ETM+, SPOT HRV and HRVIR, IRS LISS, CBERS IRMSS, and Terra ASTER can provide higher-resolution information and more accurate classifications. IKONOS and QuickBird provide the highest resolution but at the highest cost as well.

To date there are no ongoing programmes for monitoring change in the global extent of dry and



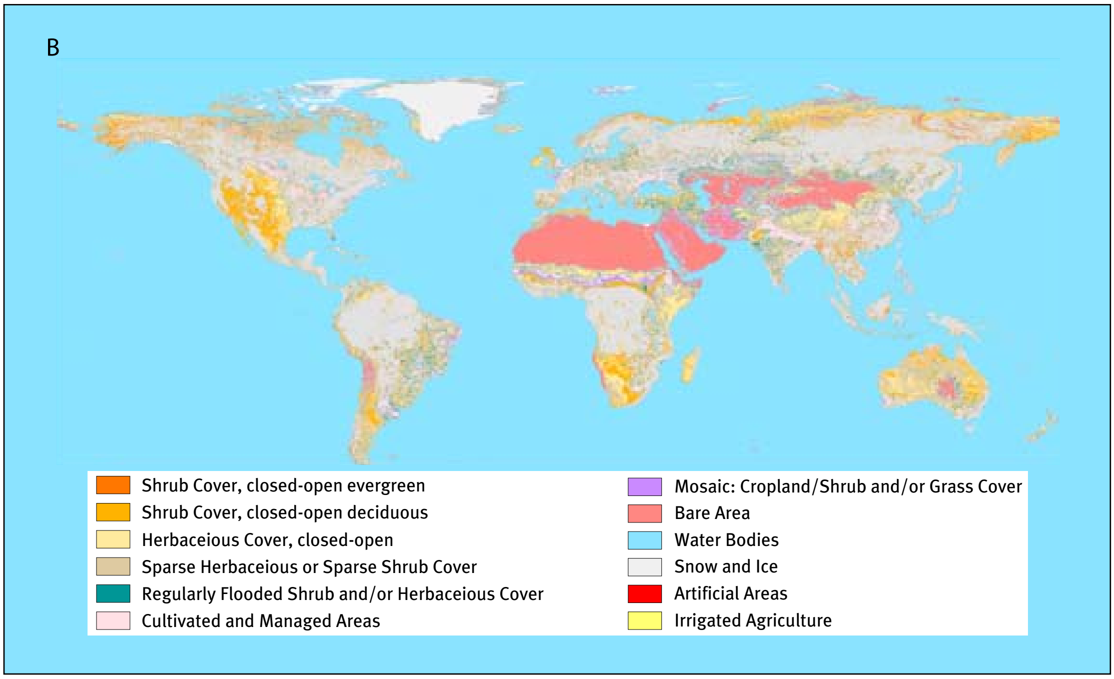


FIGURE 5.1A Map of aridity zones according to Deichmann and Eklundh (1991) (Gray background represents humid zone. No data above 60 degrees north and south. B Map of land cover classes derived from satellite data that correspond to dry and sub-humid ecosystems. (Bartholomé and Belward 2005).

sub-humid lands. Existing global land cover maps, such as GLC2000 (Bartholomé and Belward 2005), GLCCD (Loveland et al. 2000), and the University of Maryland global land cover classification (Hansen et al. 2000) do not have sufficient resolution or accuracy for either global or regional monitoring needs, although they are useful for establishing approximate area and distribution for one time period. Classifications for these maps are mostly based on associations with the Normalized Difference Vegetation Index (NDVI). Minimum annual red reflectance, peak annual NDVI, and minimum channel three brightness temperature were among the most used metrics for the University of Maryland map. Accuracies hover around 80 percent overall, with most errors in drylands occurring as a result of confusion between grasslands and croplands or grasslands and wooded grasslands. Even if repeated over time, only dramatic changes across large areas or in smaller, well-sampled areas could be detected from these mapping efforts.

5.1.1 Local and regional extent and change

General trends in the extent of dryland ecosystems can be examined over time by correlating variables such as reflectance values, principal components, band ratios from multitemporal satellite data such as AVHRR and MODIS with known or estimated values from the field (McDermid et al. 2005). For very small areas, the mapping of individual trees or specific grassland communities might be accomplished using high-resolution satellite data such as IKONOS and QuickBird. However, perhaps the most useful approach for biodiversity monitoring would entail the compromise between cost and accuracy that is achievable at an intermediate resolution with either Landsat or SPOT imagery. Several classification techniques are available for change analysis (supervised or unsupervised, simultaneous or postclassification—see chapter 3 on remote sensing basics). Relying exclusively on automated classifications of grasslands and other arid ecosystems is likely to produce less than optimal results. Traditional remote sensing and image interpretation techniques, which rely on visual interpretation of such cues as texture, tone, contrast, and context, are helpful in identifying and delineating individual habitats or ecosystems.

In general, accuracy levels are higher under certain conditions such as a small area of interest, strategic timing of scene acquisitions, more detailed knowledge of ground cover type, greater knowledge of local ecology, and more extensive ground truth information. Furthermore, low turnover in the soil-rock background is preferable for accuracy's sake. Under such conditions, Grignetti et al. (1997) achieved 85 percent classification accuracy in the Mediterranean and up to 95 percent among finely defined community types such as thermophile oak wood, mixed oak wood and evergreen scrubs, *Pinus pinea* woods, and agricultural areas.

5.1.2 General considerations for satellite monitoring in dry and sub-humid lands

Many of the same issues that affect the interpretation of satellite measurements in dryland regions hold true for field observations as well; therefore, they are not necessarily shortcomings of remote sensing problems per se. For example, natural transitions between savannas, grasslands, deserts and shrublands, and even forests are often gradual; this makes it difficult to draw boundaries between ecosystems or consistently determine patterns of change when observing from the field, air, or space.

In drylands, considerable natural variation in the spectral qualities of vegetation over time and between seasons makes it difficult to judge when change is significant in terms of biodiversity and natural resource management. Change in vegetation amount is closely linked with variations in local precipitation. Within a single season, storms or rainy periods may result in dramatic localized changes in plant cover. In addition to that of vegetation, spectral characteristics of communities of cyanobacteria, fungi, lichens, and mosses can change in response to such short precipitation events (Tsoar and Karnieli 1996). Ecosystems may experience more than one greenup or variable greenups from year to year (Zhang et al. 2003). Over longer time intervals, irregular events such as periodic droughts, floods or dust storms may have a dramatic effect on the spectral landscape (Muhs and Maat 1993, Schultz and Ostler 1993). These forms of natural variation can be misinterpreted or missed altogether if the timing of acquired imagery is not carefully considered. Meteorological records should be consulted to ascertain moisture conditions associated with a certain satellite image, or to choose optimal dates for a change analysis (Yang et al. 1997; Yang et al. 1998). Global climate data are available from the Global Precipitation Climatology Project (Adler et al. 2003) and from the NOAA Climate Prediction Center's Merged Analysis of Precipitation (Xie and Arkin 1997). However, at 2.5 degree resolution, these data are appropriate for regional use only. Smaller areas, such as landscapes, require a denser set of observations over space and time (Nezlin and Stein 2005). But in many dryland regions, especially in Africa, coverage of meteorological stations is too sparse for regional or local monitoring needs.

One of the biggest challenges for remote sensing in dry and sub-humid areas is that image pixels may contain little or no contribution from photosynthetic plant matter. Instead, soil, shadow, rock, senescent material, or nonphotosynthetic vegetation (NPV) may dominate – this is particularly true in hyperarid areas. It is very difficult to classify or quantify vegetation cover of less than about 40 percent because of the spectral dominance of background soils and rocks (Smith et al. 1990). To reduce this problem, spectral unmixing (mixture modelling) is used to discriminate among soil, nonphotosynthetic material, and plant material. The resulting models of percentage of land cover work reasonably well in certain locales, such as desert shrub canopies (McGwire et al. 2000). However, a significant limitation is that all significant pixel components must have unique and identifiable signatures. Second, the soil-rock background surrounding sparse vegetation may be quite heterogeneous and is unlikely to stay constant across a large area so that reflectance values have to be calibrated frequently throughout. The best results so far have been attained with hyperspectral imagery for very limited areas and when there is vegetation cover over 30% (Okin and Roberts 2004). So, although it holds promise, spectral unmixing is not yet an appropriate technique for operational monitoring.

Monitoring of large dryland regions will require the mosaicking and atmospheric correction of many Landsat images, complicating the analysis process. Images need to be matched at the edges, which can be difficult if they were not taken during the same time period. Broad-scale monitoring, stitching together dozens of Landsat images, has been used for forest monitoring, but we are not aware of efforts for grasslands at the same magnitude. This may be partially due to the fact that it is more challenging to separate grassland from agricultural areas automatically as it requires detailed and time-intensive visual interpretation or the integration of additional data sets. This is a particularly significant limitation in that agricultural expansion is one of the greatest threats to natural dry and sub-humid systems. As a result, studies measuring extent and fragmentation in drylands are likely to be limited in size.

Case study 5.1: Land cover change in Senegal

Author: adapted from Tappan et al. (2004)
Indicators: change in 13 land cover and land use classes
Potential monitoring scale: national, regional, global
Sensors: Landsat TM, ETM+ and Corona
Imagery cost/hectare: free
Limitations on accuracy: sampling vs. complete survey

a. Introduction

Tappan et al. (2004) analysed and quantified 40 years of land use and land cover changes in Senegal at three points in time—1965, 1985, and 2000. To do so, they used a combination of satellite imagery, aerial surveys, and fieldwork. Imagery was collected from Corona satellite photographs (1965 and

1968 in some cases), Landsat TM (1984–85), and Landsat ETM(+) (1999–2000). Because they started with data from the 1960s, effects of subsequent droughts and the tripling of population could be documented. Ancillary data included 1940s aerial photos from U.S. Army Air Corps, vertical and oblique colour videography, before and after photos taken at 10- to 15-year intervals at hundreds of ground monitoring sites, extensive fieldwork, aerial surveys, and interviews.

b. Method

To cut down on time and cost of interpretation, a sampling scheme was used, consisting of a random sample of 10-kilometre by 10-kilometre frames stratified by ecoregion. Ecoregions are ecological areas with similar biophysical and human management conditions (see figure 5.2). They provide a useful framework for effective research, inventory, and management of natural resources. A total of 9,310 square kilometres was chosen, from 2 to 12 frames per ecoregion equaling 4.6 percent of Senegal's total land area. Each sample frame was manually interpreted using 13 land use and land cover classes. A manual approach was preferred for working with analogue, film-based photographs. Also, interpreters were able to integrate photographic elements of tone, hue, texture, shape, size, pattern, shadow, and geographic context.

c. Results

Tappan et al. summarized the area of each class by ecoregion and by period in time. Results aggregated to the national level show moderate change, with a modest decrease in savannas from 74 to 70 percent from 1965 to 2000 and an expansion of cropland from 17 to 21 percent. However, at the ecoregional scale, they observed rapid change in riparian forests, wooded savannas, and woodlands and a sharp increase in the area of bare, unproductive soil—from 0.3 percent in 1965 to 4.5 percent in 1999. There was an almost complete agricultural transformation of the floristically diverse natural communities in the Saloum agricultural ecoregion. The results of this change assessment have helped Senegal to improve agricultural management, stabilize coastal dunes, protect remaining forest areas, and spread awareness of environmental issues.

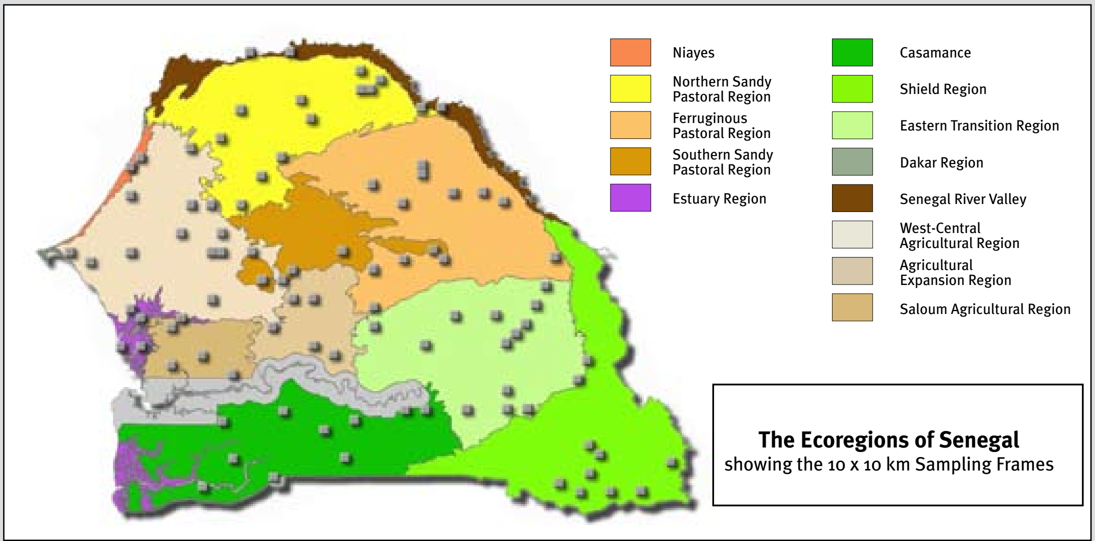


FIGURE 5.2. Small squares indicate 10-kilometre by 10-kilometre sites randomly chosen within the 13 ecoregions of Senegal.

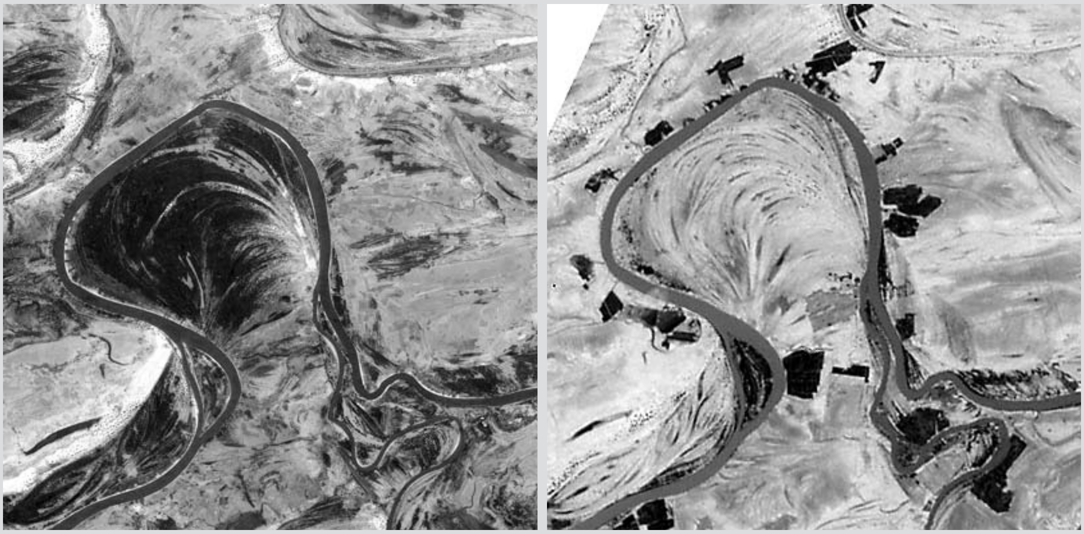


FIGURE 5.3A Corona photograph, December 1965; B TM image, January 1994. This pair of satellite images shows the total loss of riverine acacia forests at a loop in the Senegal River just west of Podor.

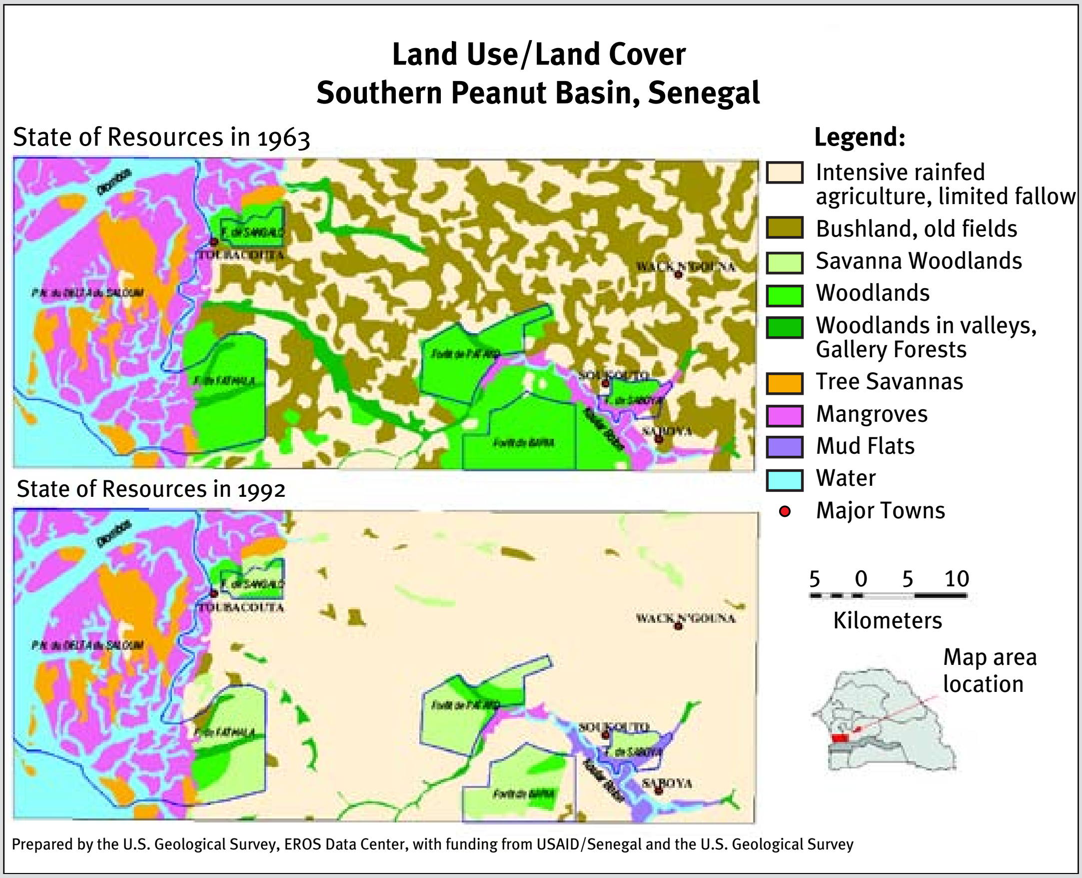


FIGURE 5.4 A pair of maps depicting the final stage of agricultural transformation in the Saloum Agricultural Region. The top map was produced from interpretations of a 1963 Argon satellite photograph while the bottom map was produced from a 1992 Landsat image.

5.2 Changes in Habitat or Ecosystem Quality

5.2.1 Degradation and desertification

Land degradation or "desertification" of dry and sub-humid areas can result from a number of factors, both natural and anthropogenic (UNCCD 1994). In the context of biodiversity monitoring, we are interested in human-induced changes, which generally result from inappropriate land uses such as intensive tillage, over-irrigation, and overgrazing. These land uses ultimately reduce vegetation and soil productivity through the loss of nutrients, soil organic matter, water-holding capacity, or a combination of these factors.

Relative indices of degradation or condition based on field and auxiliary data (for example, biomass, palatable vegetation, and biodiversity) have been correlated with spectral reflectance values derived from satellite images. Land degradation features associated with wind erosion, salinization, overgrazing, sedimentation, and extreme gullying have been mapped directly in many instances (Lantieri 2003). However, change in vegetation coverage as a result of degradation is more easily detected and interpreted from satellite imagery (Yang et al. 2005) than the various causes of degradation. For example, using TM, existing vegetation maps, and additional field surveys Tong et al. (2004) assessed steppe degradation in Inner Mongolia (China) by tracking gradual changes in the amount of intact *Stipa grandis* vegetation and degraded *Artemisisa* or *Cleistogenes* steppe.

Productivity refers to both the rate of photosynthesis and the rate of biomass accumulation and is a characterization of vegetation that remote sensing can measure reasonably well in simpler canopy structures, such as grasslands or shrublands with sufficient cover (30–40 percent). It is essential that temporal changes in productivity due to degradation are distinguished from natural variability in vegetation in response to climate. It is also important to distinguish between degradation resulting in long-term negative consequences, and the one-time clearing of vegetation.

Productivity trends are commonly derived using the NDVI (Price et al. 2002). The NDVI is calculated as a normalized ratio of the reflectance in the red and near-infrared of the electromagnetic spectrum or NDVI = (NIR — VIS)/(NIR + VIS). The red and near-infrared bands are particularly useful for monitoring vegetation thickness, health, and biomass. In more arid ecosystems, seasonally summed or integrated NDVI values are strongly correlated with vegetation production (Prince 1991; Yang et al. 1998; Wessels et al. 2004). The Enhanced Vegetation Index (EVI), a standard product of MODIS, should be considered in desert or sparse shrub environments where soil contributes significant background reflectance. Kawamura et al. (2005) calculated biomass in the Xilingol steppe in central Inner Mongolia in China using Terra/MODIS EVI. Through regression modelling, they could account for 80 percent variation of live biomass with EVI data. As the MODIS record increases in length, it will become increasingly useful for productivity monitoring.

Long-term study of multi-seasonal and multi-year data (30 to 40 years or more in length) can help characterize the range of normal, natural variation (Dregne and Tucker 1988). At present, the 30-year AVHRR record of the Global Inventory Mapping and Monitoring Studies (GIMMS) (Tucker et al. 2005) offers the most appropriate data record for studying long-term trends. The high temporal resolution of MODIS will become increasingly useful as the data record lengthens. Data from MSS, TM, SPOT, Kosmos-1939, IRS-IA and IB, and AVIRIS have also been used to assess desertification at finer resolutions (Yang et al. 2005). These data sources with higher spatial resolution but shorter collection histories can be useful for exploring driving factors in areas where degradation is known to occur.

If productivity is observed to diverge from its historical pattern, a number of causes may be considered, such as degradation, conversion to agriculture, increased use of irrigation or fertilizer, initial stages of plant invasion or even climate change (see 5.3.1). Field data and knowledge must be used alongside remotely sensed productivity measures both to calibrate and to validate the cause of change in productivity as well as the effect on biodiversity.

Figure 5.5 illustrates the considerable natural variation in productivity in Mongolia, which in turn, affects the movements and potential management for wild ungulates. In another example, grass greenness based on the NDVI was used to predict the seasonal movements of wildebeest, hartebeest, and ostrich in the Kalahari of Botswana (Verlinden and Masogo 1997). Pettorelli et al. (2005) provide more detailed explanation and references.

The Land Degradation Assessment (LADA) of the Food and Agriculture Organization (FAO) and United Nations Environment Programme (UNEP) is actively investigating the use of remote sensing for assessing land degradation at the local, national, and global levels for applications related to the UNCCD as well as the CBD. A recent FAO study (Lantieri 2003) on the practicality of remote sensing for monitoring land degradation considers the following functions to be particularly useful:

- to identify trends in vegetation activity, rainfall, soil moisture, and agricultural intensification, all of which can be associated with the desertification process
- to stratify the land surface in order to optimize field sampling for in-depth desertification studies

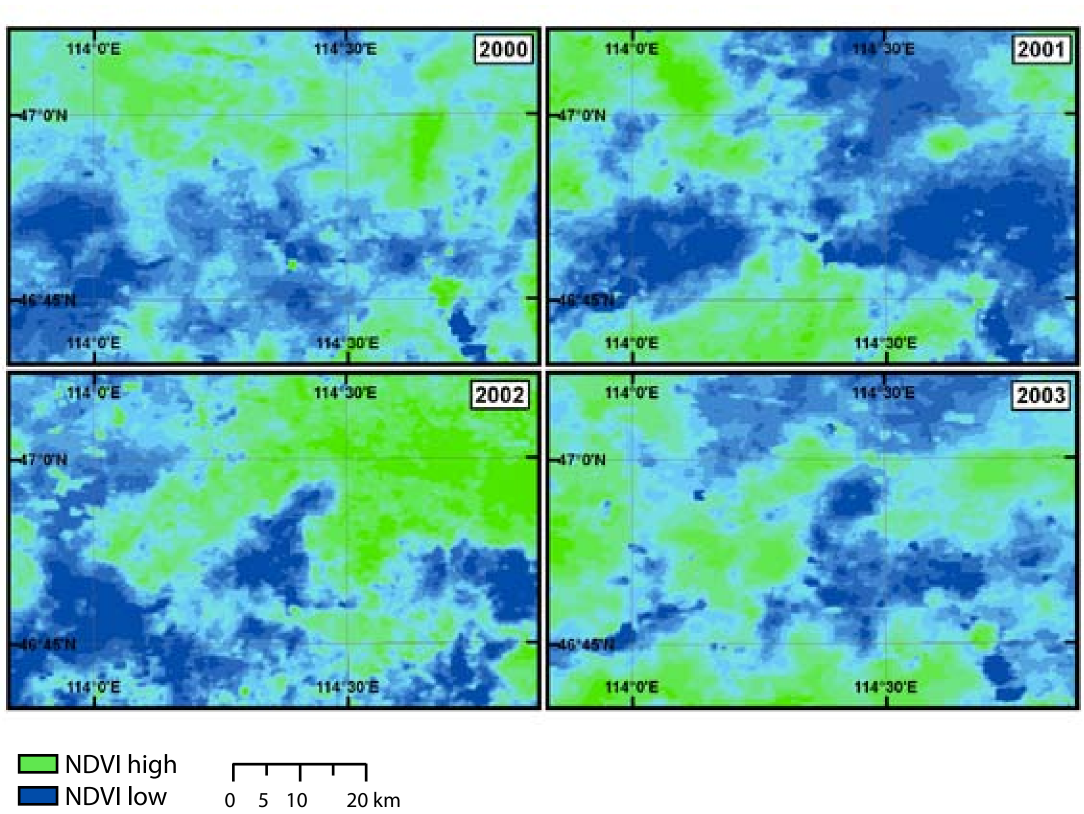


FIGURE 5.5. Spatial and temporal variability of vegetation productivity measured as NDVI from MODIS satellite imagery in eastern Mongolia at the end of June in the years 2000 – 2003. The end of June is the critical calving season for Mongolian gazelles, which are the dominant ungulate in the eastern steppes. Extreme resource variability enlarges their area needs and makes their conservation within single protected areas ineffective. They require landscape level management plans which can be informed by dynamic habitat models based on NDVI imagery (e.g., Mueller et al. submitted).

- to map directly many areas under some specific desertification process (such as wind erosion patterns, salinization patterns [salt may be visible as white patches], overgrazing features shown by low-cover grasslands around animal paths, sedimentation of lakes or rivers [see chapter 7] and large areas of soil water erosion [gullies])

Many experts believe that routine monitoring may be premature in the LADA context. Methods or consensus on how to establish a baseline condition from which to define degradation are still unresolved issues. More information, including the experience of measuring degradation in the countries of China, Senegal, and Australia, is available on LADA's Web site (http://lada.virtualcentre.org/pagedisplay/display.asp).

5.2.2 Ecosystem integrity

Dry and sub-humid ecosystems often harbor highly mobile species—especially mammalian herbivores—that are seasonal migrants. Fragmentation or the appearance of unnatural barriers can obstruct migratory movements of such migrants, disrupting their life cycles and ultimately severely reducing their populations (Ito et al. 2005). Their mobile lifestyle generally increases their vulnerability to fragmentation and land use changes (Berger 2004). In some cases migration routes are predictable and have been protected through the alleviation of other pressures, which for example has led to increasing populations of mammalian herbivores in sub-Saharan Africa. In other cases movement routes of populations are variable and difficult to predict which makes them especially difficult to protect (e.g. Mongolian gazelles, Mueller et al. submitted). For issues and methods for detecting and monitoring fragmentation, see chapter 10.

Community intactness might be considered an inverse measure of degradation and represents undisturbed areas with natural levels of biodiversity. Muldavin et al. (2001) found greater richness and abundance of noninvasive and nonruderal plant species to be associated with low-disturbance grasslands with lower shrub abundance, greater litter and grass cover, and less exposed soil. They developed a biodiversity index using TM reflectance values as independent values to predict grass, shrub, litter, and soil cover. As exposed soil and shrub values decrease, litter and grass values increase and, consequently, the biodiversity index goes up. Assuming that biodiversity increased when grass and litter were high and decreased in areas with significant quantities of shrubs or bare ground, a spatial map of biodiversity value results.

Chen et al. (2005) suggest a different method for measuring community intactness in a desert environment. They used Landsat ETM+ data to observe biological soil crusts that consist of communities of mosses, lichens, liverworts, algae, fungi, cyanobacteria, and bacteria. Erosion or inappropriate land use destroys these cryptobiotic crusts, thus their presence and distribution can be an important indicator of desert integrity and biodiversity. Using Landsat ETM+, the authors concluded that if at least 33 percent of a pixel is crust, they can identify it with a Kappa coefficient of 0.82 and overall accuracy of 94.7 percent in a desert environment.

Dry and sub-humid lands feature many ecosystem characteristics whose integrity is not measurable from space. In these cases, field monitoring is more appropriate. For example, many areas support high concentrations of endemic species. This is especially true of Mediterranean landscapes such as the Cape Floral Kingdom of Southern Africa and the Mediterranean Basin. Intact fauna is also not detectable if overhunting has occurred. Therefore, it is important to adopt multiple methodologies in order to develop an accurate picture of biodiversity intactness in any particular place.

5.2.3 Monitoring ecological processes in dry and sub-humid lands

Most ecosystems undergo annual or longer-term changes that can be quite dramatic, including green-up, periodic flooding, fires, and droughts. In many cases, these periodic events are part of the natural ecosystem dynamics and should not be considered detrimental to the overall grassland condition. However, as human influence on dry and sub-humid environments increases and climatic changes become more pronounced, there may be an alteration in intensity and frequency of these periodic events, ultimately leading to a degradation of or decline in sensitive ecosystems.

Regular monitoring of natural periodic changes in dry and sub-humid lands is best accomplished at a coarse scale by use of high-temporal-resolution satellite data, such as AVHRR and MODIS, and especially NDVI data sets derived from these images. The techniques are effectively identical to the ones previously discussed, where field-based conditions are related to spectral reflectance using different regression techniques. Again, AVHRR proves to be most useful because NDVI data sets for this sensor date back to the early 1980s, allowing for longer-term time series analysis of climatic, drought, and fire patterns and changes.

MODIS thermal anomalies products (one-kilometre spatial resolution) provide fire data, which are particularly important for grasslands; fire occurrence (day or night), fire location, and an energy calculation for each fire are available and can be used as indicators for drylands where fires, either man-made or naturally occurring, occur frequently. The temporal resolution of this data set ranges from near real-time daily imagery to eight-day and monthly composites. Online sources for fire occurrence information from satellites are described at the end of this chapter.

Case study 5.2: Remote sensing of fire disturbance in the Rungwa Ruaha landscape, Tanzania

Authors: Jessica Forrest, Eric Sanderson, Pete Coppolillo and Guy Picton Phillipps
Indicators: fire occurrence and extent
Potential monitoring scales: landscape, regional, global
Sensor: MODIS
Cost of imagery: free
Limitations on accuracy: cloud cover, heavy smoke, sun glint, fires smaller in area than 100 square metres

a. Introduction

The Rungwa Ruaha landscape is a vast area of approximately 40,000 square kilometres, roughly the size of Denmark. This savanna-woodland ecosystem harbors a broad range of wildlife, including hippopotamus (*Hippopotamus amphibious*), giraffe (*Giraffa camelopardalis*), bushbuck (*Tragelaphus scriptus)*, as many as 12,000 elephants (*Loxodonta africana*), and an intact carnivore guild, including Africa's third largest population of the critically endangered wild dog *(Lycaon pictus)*. The Rungwa Ruaha landscape has evolved with fire, emerging from both natural and human causes. Today, most fire in the landscape can be traced to human sources, particularly ecosystem management strategies involving the use of fire, burns set to facilitate hunting, and wildfires emerging from local settlements. We wanted to know whether the amount and patterns of burning change from year to year, from season to season, and according to jurisdiction.

b. Method

In order to study patterns of fire in the Rungwa Ruaha landscape, MODIS/TERRA thermal Anomalies/Fire eight-day L3 global one-kilometre grid data were downloaded from the U.S. Geological Survey (USGS) Web site (http://edcdaac.usgs.gov/modis/dataproducts.asp for the 2000, 2001, 2002, 2003, and 2004 dry seasons (April to December), with an image center point of 35.22 degrees longitude, −5.02 degrees latitude. Using ERDAS Imagine software, images were batch imported and reprojected to UTM Zone 36 North. Flash Renamer 4.62 was used to rename files according to their date of capture. The files were then exported to ArcInfo grid format and further processed, using the Spatial Analyst extension in ArcView 3.2, to construct grid files that indicate whether a given grid cell showed active fire in a given year and during which week(s) the fire occurred. Estimations of area burned by time and jurisdiction were then produced using ArcView. The results are expected to underestimate fire frequency, because the data were not adjusted to take into account cloud cover and no-data values. Such adjustments would have required the incorporation of cloud and missing data information from the daily MODIS/TERRA Thermal Anomalies/Fire data, also available from the USGS, into the estimates.

c. Results

Results show the impressive extent of fire activity in the Rungwa Ruaha landscape. In one year, 2004, at least 10 percent of the total landscape burned, and when we looked back over the past five years, we found with remote sensing that nearly 40 percent of the total landscape burned at least once. (See figure 5.6). At the highest end, we found that 60 percent of the Rungwa Game Reserve, an area known for its trophy hunting, had burned in the past five years. Lunda Mkwambi Wildlife Management Area showed the lowest total area burned, at 8 percent. Surprisingly, the national park itself reflected the landscape average for area burned over the past five years, with an estimated area of just under 40 percent. We noted that amount of area burned in each jurisdiction did not appear to be clearly increasing or decreasing over the years, but that there was evidence of interannual

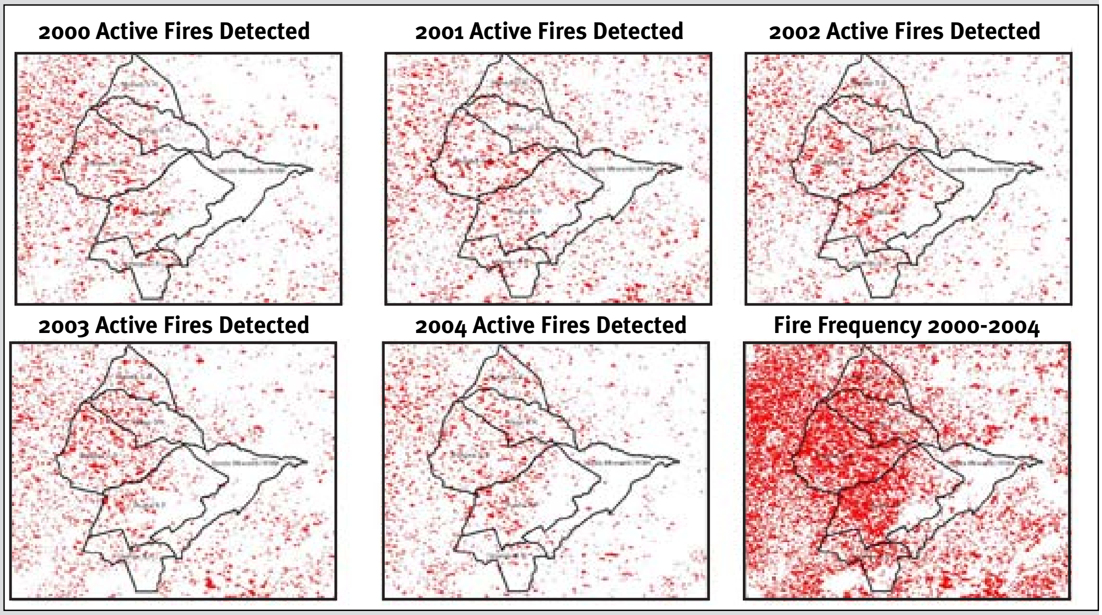


FIGURE 5.6. Dry season active fires detected with MODIS Active Fire product in the Rungwa Ruaha landscape, 2000-2004 (Map by: G. Picton Phillipps, WCS)

variation in total area affected by fire. We found that in 2003, an area was likely to burn early in the dry season (from April through June) rather than later in the season, from July through December.

d. Limitations

There are some limitations to detecting fire activity indicators at coarse scales. When we compared a MODIS image used for our analysis with a higher-resolution Landsat image gathered during the same week, we noted that the area burned (shown by the Landsat image) was in fact larger than the MODIS active fire data indicated (Figure 5.7). This is because the MODIS satellite, in its orbit, takes snapshots of active fires only two times a day, underestimating the total area affected by the fire. Frequent cloud cover and gaps between image swaths can also lead to

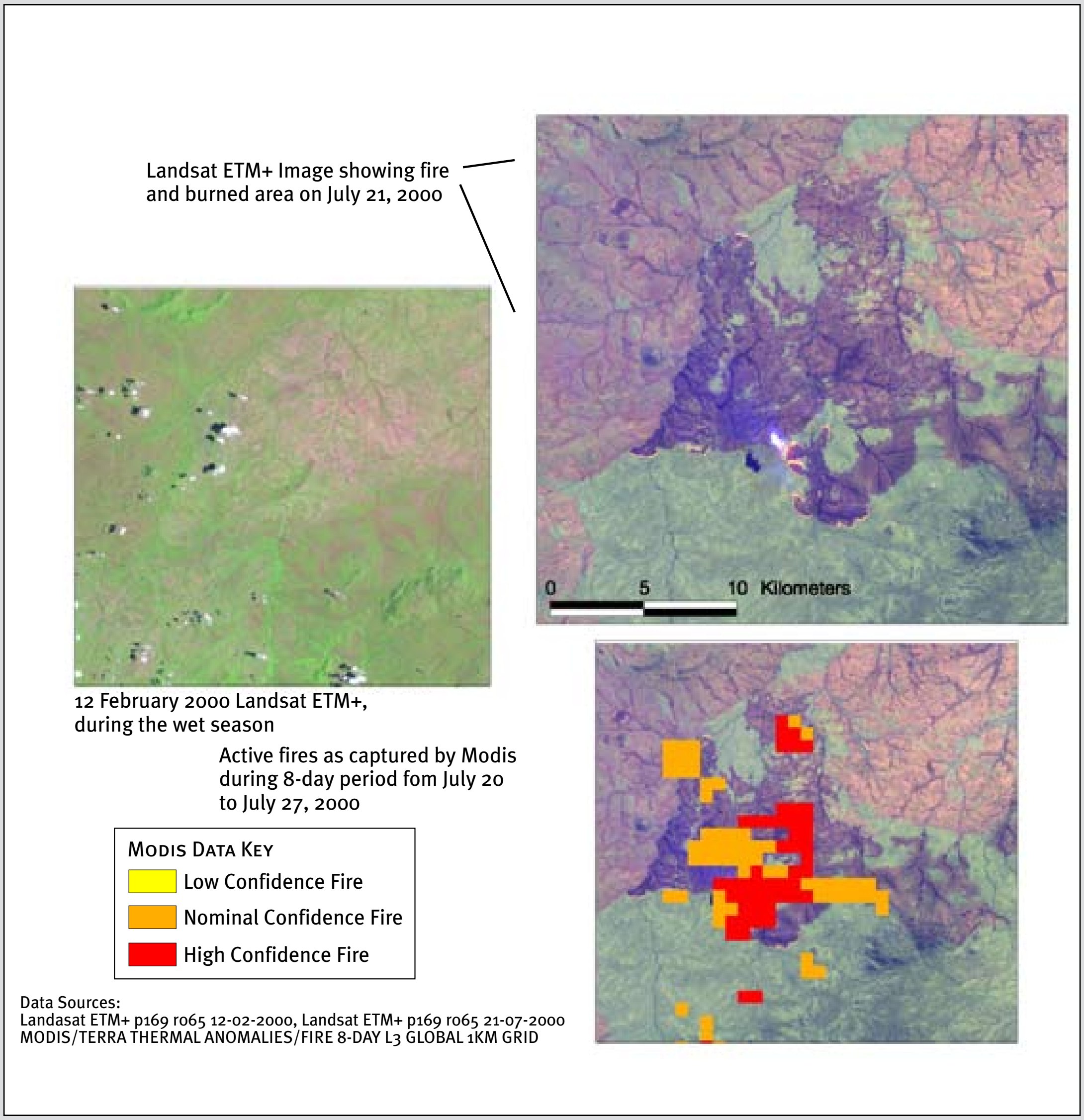


FIGURE 5.7. A comparison of MODIS Active Fire and Landsat ETM+ data for detecting total area burned by a July 21, 2001 fire in Ruaha National Park, Tanzania. (Map by: J. Forrest, WCS)

underestimates of total area affected; however, fire estimates can be adjusted for these factors. Although it is often possible to underestimate area affected by large and fast-moving fires, both nondetection and overestimation are also at issue. At one-kilometre resolution, the MODIS fire algorithm is capable of detecting only medium- to large-size fires, with smaller fires going undetected. Indeed, ground truth studies suggest that under perfect conditions, the minimum size of a detectable fire is approximately 50 square metres. Perfect conditions are those where the fire is observed at or near nadir on a fairly homogeneous surface, no other significant fires are nearby, and the scene is free of clouds, heavy smoke and sun glint. Under normal, less than perfect conditions, however, larger fires of 100 square metres are detectable only about 50 percent of the time. Once detected, however, these subpixel-scale fires will be overrepresented by one-kilometre grid cells (University of Maryland 2005). A final limitation is that the MODIS Active Fire product does not provide information on fire intensity, which has obvious implications for ecosystem regeneration and biodiversity. Intensity information can, however, be derived from the raw multispectral data itself (Kaufman et al. 2003). It is also possible to estimate fire intensity from environmental information, such as time of year and day, greenness index (or NDVI derived from satellite imagery), precipitation, temperature, wind speed, soil moisture, and vegetation type (Systems for Environmental Management [SEM] 2005).

Phenology refers to seasonal changes in organisms—such as leafing out, flowering, or senescence—in relation to climate. Phenologic changes in vegetation are easily observable in dry and sub-humid ecosystems when appropriate temporal resolution of satellite imagery is used. Examples of phenological indicators include start of growing season, end of growing season, length of growing season, length of dormancy, or date of maximum plant maturity. The NDVI or some other index of vegetation amount is typically used to determine phenological information. Periodic temporal changes in vegetation phenology, such as greening up and senescence throughout the year, can be used to classify certain ecosystem types with known phenological patterns.

Examples of phenological indicators include start of growing season, end of growing season, length of growing season, length of dormancy, or date of maximum plant maturity; these are all characteristics which can be observed on the ground. Meanwhile, remote sensing measures land surface phenology. The exact relationship between remotely sensed land surface phenology and plant or vegetation phenology cannot be universally generalized; therefore, White and Nemani (2006) recommend that land surface phenology be described as an integration of changing patterns in snowmelt, soil wetness and vegetation development and other processes.

Significant changes in land surface phenological patterns may indicate that conversion or invasion has occurred. Shifting of phenological patterns over time can provide evidence of climate change.

Yu et al. (2004) demonstrated interannual variations of the grassland-desert boundaries in the Gobi Desert by looking at the presence or absence of the onset of green-up. In contrast to grassland environments, the desert showed no measurable green-up in spring. The desert margin displayed a steppe-like phenological pattern in a wet year and a desert-like pattern in a dry year demonstrating the difficulty of classifying such areas when using images from a single time period. In another example, Peters et al. (1997) were successful in differentiating grass from shrub and from grass-shrub mix based on phenological patterns in New Mexico.

5.3 Occurrence and Distribution of Threats to Biodiversity

The CBD Programme of Work on the biological diversity of dry and sub-humid lands mentions a number of pressures on biodiversity. Some of these—such as climate change, fragmentation, overgrazing, and agricultural conversion—produce conditions that can be observed from space. Fragmentation and alien species are discussed more thoroughly in chapters 10 and 11; climate change and overgrazing are discussed in this section.

5.3.1 Climate change

Long-term changes in temperature and rainfall patterns can have serious impacts on the biological diversity of dry and sub-humid lands. Because rainfall information is not collected at a sufficiently fine resolution in most parts of the world, many consider it useful to turn to the NDVI as a proxy for rainfall. Several authors have made the link between climate change and long-term increases in the NDVI (Gray and Tapley 1985; Tucker et al. 1985; Townshend and Justice 1986; Nicholson et al. 1990; Tucker et al. 1991; Tucker and Nicholson 1999).

The GIMMS eight-kilometre, 15-day composite at maximum value is the best existing satellite-derived data set for monitoring climate change using the NDVI (Tucker et al. 2004). Anyamba and Tucker (2005) used this data set to illustrate variation and trends in vegetation and precipitation in the Sahel. Using an established relationship between precipitation and the NDVI, Tucker and Nicholson (1999) found that the NDVI reflected drought conditions during the 1980s and then higher, greener values from the 1990s to 2003. Although they observed year-to-year and decadal variations, there was no evidence of a systematic increase in desertification. Thus, climate and permanent land cover change in the Sahel were not substantiated for this 23-year period on the basis of the remotely sensed record. Osborne and Woodward (2001) applied this relationship to Mediterranean shrublands, observing a long-term increase in the NDVI from 1981 to 1991. They attributed this change to a rise in both precipitation and atmospheric carbon dioxide based on validation using a mechanistic model of vegetative growth and a database of observed climate.

The establishment of the relationship between NDVI and rainfall variation led to the remote sensing drought monitoring and the development of famine early-warning systems (Henricksen and Durkin 1986, Tucker and Choudhury 1987, Hutchinson 1991, Gonzales 2002). Famine is likely to increase unsustainable use of scarce natural resources, thus it is conceivable that famine or drought predictors double as a warning system for potential biodiversity loss as well as for human suffering.

5.3.2 Overgrazing

Changes in evolutionary levels of grazing intensity and selectivity will inevitably change biodiversity. Undergrazing and overgrazing can both have negative effects, but overgrazing by livestock is generally more problematic throughout dry and sub-humid lands. Vegetation indices have often been used to document reduced levels of productivity associated with overgrazing as well.

NDVI in particular has been used to measure bush encroachment associated with grazing. In Botswana, degraded areas include those suffering from bush encroachment, a result of heavy cattle grazing over a number of years. Using Landsat MSS, Yool et al. (1997) found that replacement of grasslands by woody species was possible. In a study with contradicting results Moleele et al. (2001) note the limitations of NDVI in terms of browse or woody biomass vegetation.

Gibbens et al. (2005) demonstrated the utility of combining historical and satellite records to show changes in community type associated with grazing. They mapped reconstructions of historical data produced in land surveys around 1900 and compared them to aerial photos from 1996. They estimated a 20 percent increase in area dominated by creosote bush, tarbush, and especially mesquite and a decrease from 19 percent to 1.2 percent of dominant native black grama. An overabundance of cattle is suspected to be the main cause.

The work of Pickup et al. (1998) in central Australia has shown associations between ground cover and vegetation cover indices derived from Landsat MSS and TM. They describe how trends in rangeland condition can be monitored by looking at changes over time in the pattern or vegetation growth across gradients of differing grazing intensity. Vegetation growth was assigned remotely sensed vegetation index values before and after large rainfalls. A vegetation ratio was derived by comparing areas less than four kilometres from water (shown to be an area of intense grazing) with low grazing benchmark areas farther away. Systematic changes in this ratio constitute a trend. Where the ratio decreases over time, the grazing gradient is intensifying and the landscape is degrading. Where the ratio increases, the landscape is becoming more resilient and the grazing gradient is disappearing.

5.3.3 Land use change

The most common type of conversion in dry and sub-humid lands occurs in cropland. A sudden shift from natural area to active agriculture can be relatively easy to detect by satellite in deserts. Crops generally have low reflectance in the visible—and high reflectance in the NIR—parts of the spectrum; desert plants feature brighter visible reflectances and lower NIR reflectances (Okin and Roberts 2004, Okin et al. 2001, Ehleringer and Bjorkman 2005). These differences, together with the shape and spatial pattern of patches of crops, often help to differentiate them from other land cover types. However, in grasslands, crops such as wheat or rye often cannot be differentiated unless sufficiently high spatial resolution allows for the detection of crop rows and field borders. Activities such as tillage, planting, and harvest of crops can create rapid seasonal changes in reflectance patterns; therefore, phenological profiles derived from remote sensing data are useful indicators of change. Delineation of changed areas can be assisted by, and may require, knowledge of crop calendars to guide remote sensing data selection and interpretation.

5.3.4 Invasive alien species

Effective management of invasives requires accurate knowledge of their spatial distribution and density. Invasive plants with phenological patterns or spectral signatures distinct from the surrounding landscapes make good candidates for remote sensing detection. Dense growth patterns also improve detection accuracy. In most drylands, the lack of an upper canopy facilitates the detection of invasion by remote sensing.

Aerial photography has been useful for monitoring invasives in relatively small areas. It is especially useful for riparian invasion given the linear nature of rivers and streams. See Everitt et al. (2001) for an example of how *Tamarix chinensis* has been mapped in the American southwest using aerial photography. Hyperspectral imagery increases the odds of finding unique spectral signatures. Using AVIRIS at an altitude for 20 x 20 m pixel size and a threshold value of 10 percent coverage per pixel, Parker and Hunt (2004) predicted the occurrence of leafy spurge with an overall accuracy of 95 percent.

Coarser scale satellite data can be used to detect invasives. However, there is a decrease in accuracy and therefore feasibility for monitoring. Bradley and Mustard (2005) investigated cheat grass, an invasive annual with higher interannual variability than native vegetation. An amplified response outside 95 percent confidence interval for native changes in NDVI was used to indicate cheat grass. Upon validation, it was shown that NDVI-TM accurately identified 72 percent of cheatgrass cover while AVHRR identified 64 percent. For more information on monitoring invasives, see chapter 11.

5.4 Data and other resources

MODIS NDVI/EVI

MODIS data are best suited for the monitoring of large areas that may exhibit interannual and annual changes in vegetation cover. Two useful and publicly available data sets based on MODIS imagery are NDVI and EVI which are compiled as biweekly mosaics. The compilation reduces problems from cloud cover and provides a short enough time period to avoid missing major phenological changes. The data can be downloaded at no charge from NASA's Earth Observing System (EOS) Data Gateway:

http://edcimswww.cr.usgs.gov/pub/imswelcome/.

Fire Occurrence and History

Fire data, including one- and eight-day composites showing fire anomalies, are compiled from MODIS data and are available at

http://edcdaac.usgs.gov/modis/dataproducts.asp.

The European Space Agency's *ATSR World Fire Atlas* provides monthly global fire maps from 1995 to the present. Data are available at

http://dup.esrin.esa.int/ionia/wfa/index.asp.

Global Inventory Modeling and Mapping Studies (GIMMS)

The GIMMS NDVI data set represents the best available long-term global record of the normalized difference vegetation index. The NDVI is a measure of vegetative greenness that has been correlated with environmental observations associated with productivity and land cover. Data are available from two online sources:

http://ltpwww.gsfc.nasa.gov/gimms/htdocs/

and http://glcf.umiacs.umd.edu/data/gimms/

Land Degradation Assessment in Drylands (LADA)

The LADA project develops and tests effective assessment methodologies for land degradation in drylands using a variety of tools, including remote sensing. The ultimate goal is to help the global community improve policies and implement international agreements and conventions such as the UNCCD and CBD. This partnership based effort is led by GEF, UNEP, FAO, and the Global Mechanism of UNCCD. This site includes a report on the *Potential Use of Satellite Remote Sensing for Land Degradation Assessment in Drylands* (Lantieri 2003) and results from pilot assessments in China, Argentina and Senegal, which have already integrated remote sensing into their measurement activities.

http://www.fao.org/ag/agl/agll/lada/default.stm

United States Geological Survey Digital Spectral Library

Researchers at the Spectroscopy Laboratory have measured the spectral reflectance of hundreds of materials in their lab and compiled a spectral library. The libraries are used as references for material identification from remote sensing images.

http://speclab.cr.usgs.gov/spectral-lib.html

Climate Data Sets

Global climate data are available from the Global Precipitation Climatology Project (Adler et al. 2003) and from the CPC Merged Analysis of Precipitation (Xie and Arkin 1997). However, at 2.5 degree resolution, these data are appropriate for regional use only. Smaller areas, such as landscapes, require a denser set of observations over space and time (Nezlin and Stein 2005).

http://www.cgd.ucar.edu/cas/guide/Data/xiearkin.html

http://www.gewex.org/gpcp.html

5.5 References

Adler, R. F., G. J. Huffman, A. Chang, R. Ferraro, P. Xie, J. Janowiak, B. Rudolf, U. Schneider, S. Curtis, D. Bolvin, A. Gruber, J. Susskind, and P. Arkin. 2003. The Version 2 Global Precipitation Climatology Project (GPCP) Monthly Precipitation Analysis (1979-present). Journal of Hydrometeorology. 4:1147–67.

Anyamba A., and C. J. Tucker. 2005. Analysis of Sahelian vegetation dynamics using NOAA-AVHRR NDVI data from 1981–2003. Journal of Arid Environments 63:596–614.

Bartholomé, E., and A. S. Belward. 2005. GLC2000: a new approach to global land cover mapping from Earth. International Journal of Remote Sensing 26:1959–77.

Berger, J. 2004. The last mile: How to sustain long-distance migration in mammals. Conservation Biology 18 (2): 320–331.

Bradley B. and J. Mustard. 2005. Identifying land cover variability distinct from land cover change: Cheatgrass in the Great Basin. Remote Sensing of Environment 94: 204–213.

Chen, J., M. Y. Zhang, L. Wang, H. Shimazaki, and M. Tamura. 2005. A new index for mapping lichen-dominated biological soil crusts in desert areas. Remote Sensing of Environment 96:165–75.

Convention on Biological Diversity. 2005 Decision VII/2 on the Biological Diversity of Dry and Sub-Humid Lands. http://www.cbd.int/doc/decisions/COP-07-dec-en.pdf

Deichmann, U., and L. Eklundh. 1991. Global digital data sets for land degradation studies: A GIS approach. GRID Case Study Series No. 4, UNEP/GEMS and GRID, Nairobi.

Demaria, M. A, W. J. McShea, K. Koy, and N. O. Maceira. 2003. Pampas deer conservation with respect to habitat loss and protected area considerations in San Luis, Argentina. Biological Conservation 115:121–30.

Dregne, H. E., and C. J. Tucker. 1988. Desert encroachment. Desertification Control Bulletin 16:16–19.

Ehleringer, J.R., and O. Björkman. 2005. Pubescence and leaf spectral characteristics in a desert shrub, Encilia farinosa, Oecologia, 36:151-162.

Everitt J.H., D.E. Escobar, M.R. Davis. 2001. Reflectance and image characteristics of selected noxious rangeland species. Journal of Range Management 54:A106–A120.

Gibbens, RP, R.P. McNeely, K.M. Havstad, R.F. Beck, B. Nolen. 2005. Vegetation changes in the Jornada Basin from 1858 to 1998. Journal of Arid Environments 61: 651–668.

Gonzales, P. 2002, Program to monitor impacts of desertification and climate change in Africa, Famine Early Warning System Network (FEWS NET), U. S. Geological Survey

Gray, T., and B. D. Tapley. 1985. Vegetation health: Nature's climate monitor. Advances in Space Research 5(6):371–7.

Grignetti, A., R. Salvatori, R. Casacchia, and F. Manes. 1997. Mediterranean vegetation analysis by multi-temporal satellite sensor data. International Journal of Remote Sensing 18(6): 1307–1318

Hansen, M. C., R. S.Defries, J. R. G. Townshend, and R. Sohlberg. 2000. Global land cover classification at 1 km spatial resolution using a classification tree approach. International Journal of Remote Sensing 21(6):1331–64.

Henricksen, B.L., and J.W. Durkin. 1986. Growing period and drought early warning in Africa using satellite data. International Journal of Remote Sensing 7 (11):1583–1608.

Hutchinson, C.F. 1991. Uses of satellite data for famine early warning in sub-Saharan Africa. International Journal of Remote Sensing 12(6):1405–1421.

Intergovernmental Panel on Climate Change. 2004. Good practice guidance for land use, land-use change and forestry. http://www.ipcc-nggip.iges.or.jp/lulucf/cop9/Chp2/Chp2_COP9.pdf (accessed March 2007)

Ito, T. Y., N. Miura, B. Lhagvasuren, D. Enkhbileg, S. Takatsuki, A. Tsunekawa, and Z. Jian. 2005. Preliminary evidence of a barrier effect of a railroad on the migration of Mongolian gazelles. Conservation Biology 19: 945–48.

Kaufman, Y. J., C. Ichoku, L. Giglio, S. Korontzi, D. A. Chu, W. M. Hao, R. R. Li, and C. O. Justice. 2003. Fire and smoke observed from the Earth Observing System MODIS instrument—products, validation, and operational use. International Journal of Remote Sensing 24(8):1765–81.

Kawamura, K., T. Akiyama, H. Yokota, M. Tsutsumi, T. Yasuda, O. Watanabe, G. Wang, and S. Wang. 2005. Monitoring of forage conditions with MODIS imagery in the Xilingol steppe, Inner Mongolia. International Journal of Remote Sensing 26:1423–36.

Lantieri, D. 2003. Potential use of satellite remote sensing for Land Degradation Assessment in Drylands. Application to the LADA Project, FAO, Rome. http://lada.virtualcentre.org/eims/approver/pub_dett.asp?pub_id=92920&app=0&section=method (accessed July 2006).

Loveland, T. R., B. C. Reed, J. F. Brown, D. O. Ohlen, Z. Zhu, L. Yang, and J. W. Merchant. 2000. Development of a global land cover characteristics database and IGBP DISCover from 1 km AVHRR data. International Journal of Remote Sensing 21:1303–30.

McDermid, G. J., S. E. Franklin, and E. F. LeDrew. 2005. Remote sensing for large-area habitat mapping. Progress in Physical Geography 29(4):449–74.

McGwire, K. L., T. Minor, and L. Fenstermaker. 2000. Hyperspectral mixture modeling for quantifying sparse vegetation cover in arid environments. Remote Sensing of Environment 72(3):360–74.

McNaughton, S. J. 1985. Ecology of a grazing ecosystem—the Serengeti. Ecological Monographs 55:259–94.

McNaughton, S. J. 1993. Grasses and grazers, science and management. Ecological Applications 3:17–20.

Middleton, N. J., and D. S. G. Thomas, eds. 1992. World atlas of desertification. 2nd ed. London: Edward Arnold.

Millennium Ecosystem Assessment, 2005. Ecosystems and Human Well-being: Biodiversity Synthesis. World Resources Institute, Washington, DC.

Moleele, N., S. Ringrose, W. Arnberg, B. Lunden, C. Vanderpost. 2001. Assessment of vegetation indexes useful for browse (forage) prediction in semi-arid rangelands. International Journal of Remote Sensing 22(5):741 – 756.

Mueller T., K. Olson, P. Leimgruber, G. B. Schaller, M. G. Murray, and T. K. Fuller. Submitted for publication. In search of forage: Predicting dynamic habitats of migrating Mongolian gazelles using satellite estimates of biomass productivity. Journal of Applied Ecology.

Muldavin, E. H., P. Neville, and G. Harper. 2001. Indices in grassland biodiversity in the Chihuahuan Desert ecoregion derived from remote sensing. Conservation Biology 15:844–55.

Muhs, D. R., and P. B. Maat. 1993. The potential response of Great Plains eolian sands to greenhouse warming and precipitation reduction on the Great Plains of the U.S.A. Journal of Arid Environments 25:351–61.

Nezlin, N. P., and E. D. Stein. 2005. Spatial and temporal patterns of remote sensed and field-measured rainfall in southern California. Remote Sensing of Environment 96(2):228–45.

Nicholson, S. E., M. L. Davenport, and A. R. Malo. 1990. A comparison of vegetation response to rainfall in the Sahel and East Africa, using Normalized Difference Vegetation Index from NOAA AVHRR. Climate Change 17:209–41.

Okin, G. S., and D.A. Roberts. 2004. Remote sensing in arid regions: Challenges and opportunities. In Remote sensing for natural resources management and environmental monitoring: manual of remote sensing, vol. 4, 3rd ed., ed. Susan Ustin. NJ: John Wiley & Sons.

Okin, G.S., W.J. Okin, B. Murray, and D.A. Roberts. 2001. Practical limits on hyperspectral vegetation discrimination in arid and semiarid environments, Remote Sensing of Environment, 77:212-225.

Osborne, C. P., and F. I. Woodward. 2001. Biological mechanisms underlying recent increases in the NDVI of Mediterranean shrublands. International Journal of Remote Sensing 22(10):1895–1907.

Parker, A.E. and E.R. Hunt, Jr. 2004. Accuracy assessment for detection of leafy spurge with hyperspectral imagery Journal of Range Management. 57:106-112.

Peters, A., M. K. Eve; E. H. Holt, and W. G. Whitford. 1997. Analysis of desert plant community growth patterns with high temporal resolution satellite spectra. Journal of Applied Ecology 34(2):418–32.

Pettorelli, N., J. O. Vik, A. Mysterud, J. M. Gaillard, C. J. Tucker, and N. C. Stenseth. 2005. Using the satellite-derived Normalized Difference Vegetation Index (NDVI) to assess ecological effects of environmental change. Trends in Ecology and Evolution 20(9):503-510.

Pickup, G. G.N. Bastin, and V.H. Chewings. 1998. Identifying trends in land degradation in non-equilibrium rangelands. Journal of Applied Ecology. 35: 365-377.

Price, K. P., X. Guo, and J. M. Stilles. 2002. Optimal Landsat TM band combinations and vegetation indices for discrimination of six grassland types in eastern Kansas. International Journal of Remote Sensing 23:5031–42.

Prince, S. D. 1991. Satellite remote sensing of primary production: comparison of results for Sahelian grasslands 1981–1988. International Journal of Remote Sensing 12:1301–12.

Scholes, R. J., and D. O. Hall. 1996. The carbon budget of tropical savannas, woodlands, and grasslands. In Global change: effects on coniferous forests and grasslands, SCOPE 56, ed. A. K. Breymeyer, D. O. Hall, J. M. Melillo, and G. I. Agren, 69–100. Chichester, United Kingdom: Wiley.

Schultz, B. W., and W. K.Ostler. 1993. Effects of prolonged drought on vegetation association in the northern Mojave Desert. In Wildland Shrubs and Arid Land Restoration Symposium, Las Vegas, Nevada, October 19–21, 1993, ed. B. A. Roundy, E. D. McArthur, J. S. Haley, and D. K. Mann, 228–35. General Technical Report INT-GTR-315. Ogden, Utah: U.S. Department of Agriculture, Forest Service, Intermountain Research Station.

SEM (Systems for Environmental Management). 2005. Fire.org: Public domain software for the wildland fire community. http://fire.org/index.php?option=content&task=section&id=2&Itemid=25 (accessed September 22, 2005)

Shoshany, M. 2000. Satellite remote sensing of natural Mediterranean vegetation: a review within an ecological context. Progress in Physical Geography 24(2):153–178

Smith, M. O., S. L. Ustin, J. B. Adams, and A. R. Gillespie. 1990. Vegetation in deserts: I. A regional measure of abundance from multispectral images. Remote Sensing of Environment 31:1–26.

Sörensen, Levke. 2007. A spatial analysis approach to the global delineation ofdryland areas of relevance to the CBD Programme of Work on Dry and Sub-humid Lands, Cambridge, UK: UNEP-WCMC. Page: 24 http://www.unep-wcmc.org/habitats/drylands/dryland_report_final_HR.pdf (accessed May 2007)

Tappan, G. C., M. Sall, E. C. Wood, and M. Cushing. 2004. Ecoregions and land cover trends in Senegal. Journal of Arid Environments 59(3):427–62.

Tong, C., J. Wu, S. Yong, J. Yang, and W. Yong. 2004. A landscape-scale assessment of steppe degradation in the Xilin River Basin, Inner Mongolia, China. Journal of Arid Environments 59:133–49.

Townshend, J. R. G., and C. O. Justice. 1986. Analysis of the dynamics of African vegetation using the Normalized Difference Vegetation Index. International Journal of Remote Sensing 7:1555–70.

Tsoar, H., and A. Karnieli. 1996. What determines the spectral reflectance of the Negev-Sinai sand dunes. International Journal of Remote Sensing 17:513–26.

Tucker, CJ; Choudhury, BJ 1987. Satellite Remote Sensing of Drought Conditions Remote Sensing of Environment 23 (2):243-251.

Tucker, C.J, H. E. Dregne, and W. W.Newcomb, 1991: Expansion and contraction of the Sahara desert from 1980 to 1990. Science, 253: 299–301.

Tucker, C.J., Justice, C.O., Prince, S.D., 1986. Monitoring the grasslands of the Sahel 1984–1985. International Journal of Remote Sensing 7:1571–1581.

Tucker, C. J., W. W. Newcomb, and H. E. Dregne. 1994. AVHRR data sets for determination of desert spatial extent. International Journal of Remote Sensing 15:3547–65.

Tucker, C. J., W. W. Newcomb, S. O. Los, and S. D. Prince. 1991. Mean and inter-annual variation of growing-season Normalized Difference Vegetation Index for the Sahel 1981–1989. International Journal of Remote Sensing12:1133–5.

Tucker, C. J., and S. E. Nicholson. 1999. Variations in the size of the Sahara Desert from 1980 to 1997. Ambio 28:587–91.

Tucker, C.J., J.E. Pinzon, M.E. Brown, D. Slayback, E.W. Pak, R. Mahoney, E. Vermote and N. El Saleous. 2005. An Extended AVHRR 8-km NDVI Data Set Compatible with MODIS and SPOT Vegetation NDVI Data. International Journal of Remote Sensing 26 (20) pp. 4485-4498.

Tucker, C. J., J. R. G. Townshend, and T. E. Goff. 1985. African land-cover classification using satellite data. Science 227 (4685):369–75.

UNCCD. 1994. United Nations Convention to Combat Desertification. http://www.unccd.int. (Accessed March 2006)

University of Maryland. 2005. Web Fire Mapper FAQs. http://maps.geog.umd.edu/faq.asp (accessed on 7 April 2005.)

Ustin, S. editor. 2004. Remote Sensing for Natural Resources Management and Environmental Monitoring: Manual of Remote Sensing, 3 ed., Vol. 4 ed. NJ: John Wiley & Sons, Inc

Verlinden A., and R. Masogo. 1997. Satellite remote sensing of habitat suitability for ungulates and ostrich in the Kalahari of Botswana. Journal of Arid Environments 35(3):563–74.

Wessels, K. J., S. D. Prince, P. E. Frost, and D. Zyl. 2004. Assessing the effects of human-induced land degradation in the former homelands of northern South Africa with a 1 km AVHRR NDVI time-series. Remote Sensing of Environment 91:47–67.

White, M. and Nemani, R. 2006. Real-time monitoring and short-term forecasting of land surface phenology. Remote Sensing of Environment 104: 43-49.

White, R. P., S. Murray, and M. Rohwedder. 2000. Grassland ecosystems. Washington, D.C.: World Resources Institute.

Xie, P. and P. Arkin. 1997. Global precipitation: A 17-year monthly analysis based on gauge observations, satellite estimates, and numerical model outputs. Bulletin of the American Meteorological Society 78:2539–58.

Yang, L., B. K. Wylie, L. L. Tieszen, and B. C. Reed. 1998. An analysis of relationships among climate forcing and time-integrated NDVI of grasslands over the US Northern and Central Great Plains. Remote Sensing of Environment 65:25–37.

Yang, W., L. Yang, and J. W. Merchant. 1997. An assessment of AVHRR/NDVI-ecoclimatological relations in Nebraska, USA. International Journal of Remote Sensing 18(10):2161–80

Yang, X., K. Zhang, B. Jia, and L. Ci. 2005. Desertification assessment in China: An overview. Journal of Arid Environments 63:517–31.

Yool, S. R., M.J. Makaio, and J.M. Watts. 1997, Techniques for computer-assisted mapping of rangeland change. Journal of Range Management 50:307–314.

Yu, F., K.P. Price, J. Ellis, J.J. Feddema, and P. Shi. 2004. Interannual variations of the grassland boundaries eastern edges of the Gobi Desert in central Asia. International Journal of Remote Sensing 25(2):327–46.

Zhang, X., M. A. Friedl, C. B. Schaaf, A. H. Strahler, J. C. F. Hodges, F. Gao, B. C. Reed, and A. Huete. 2003. Monitoring vegetation phenology using MODIS. Remote Sensing of Environment 84:471–75.

Chapter 6. Trends in Selected Biomes, Habitats and Ecosystems: Inland Waters

AUTHOR: Ned Gardiner[1]
CONTRIBUTORS: Ricardo Díaz-Delgado Hernández[2]
REVIEWERS: David Coates[3], Ricardo Díaz-Delgado Hernández[2]
1 American Museum of Natural History, 2 Doñana Biological Research Station, 3 Secretariat of the Convention on Biological Diversity

Remote sensing based indicators for inland waters:

- Extent of large inland waters and wetlands
- Extent of inland waters below sensor detection limits
- Variability of water levels and extent
- Coupling biological and physical assessments
- Changes in habitat and ecosystem quality

6.1 Introduction

Earth's wetlands provide priceless services to society. Wetlands deliver and cleanse fresh water, from headwater streams to receiving water bodies such as lakes, rivers, and oceans. Freshwater fisheries provide protein and food security to much of the world, especially for rural populations in developing countries where people have direct access to fishing waters and a large proportion of the catch is consumed locally with or without formal marketing arrangements (Coates 1995). Wetlands mitigate natural and anthropogenic processes. Headwater streams process nitrogen inputs from non-point sources very effectively; those smaller than 5m in width export only about half of the nitrogen inputs they receive (Peterson et al. 2001). Wetland vegetation also provides a physical barrier to storms. For example, mangroves buffered coastal areas of Sumatra struck by the tsunami of December 26, 2004 (Danielsen et al. 2005).

About 6 percent of Earth's surface is covered by freshwater ecosystems. Within that 6 percent of Earth's surface dwells much of the planet's biodiversity. Species that use freshwater habitats are threatened at greater rates than other taxa (Ricciardi and Rasmussen 1999). Systematics and taxonomy are also incomplete in the freshwater realm. Only recently has a global database of amphibians and the threats they face been available[1]. Freshwater fishes, which comprise approximately 30 percent of the planet's vertebrate biodiversity, are not well described. Hundreds of new species are described annually; thus their distributions, threats, and life histories are inadequately understood. There is good reason to believe current numbers of imperilled taxa will increase in light of ongoing findings in systematics of freshwater species. Because of the importance and imperilment of these freshwater species, international attention has recently focused on protecting and managing both inland waters and wetlands.

6.1.1 Definition of inland waters

Inland waters refers to lakes, streams, rivers and other bodies of water located within continental boundaries. The CBD supports the Ramsar definition and framework for delineating and protecting "wetlands". That definition encompasses a very wide diversity of ecosystem types:

> … areas of marsh, fen, peatland or water, whether natural or artificial, permanent or tempo-

1 http://www.globalamphibians.org

> rary, with water that is static or flowing, fresh, brackish or salt, including areas of marine water the depth of which at low tide does not exceed six metres… [These areas] may incorporate riparian and coastal zones adjacent to the wetlands, and islands or bodies of marine water deeper than six metres at low tide lying within the wetlands[2].

This chapter addresses both inland waters and wetlands (collectively termed "freshwater systems") because remote sensing and spatial analysis techniques used to study each inform one another and differ markedly from those used in terrestrial systems.

6.1.2 Feasibility of remotely sensed indicators for inland waters

Their importance and imperilment underscore the need to map and monitor freshwater systems using remote sensing as well as data collected directly from wetland habitats. When asked about the feasibility of identifying, delineating, and monitoring wetlands on a global basis using Earth observing (EO) satellites, the Chair of the European Space Agency's Earth Science Advisory Committee, Professor Hartmut Graßl, replied that global wetland monitoring is already possible, given the all-weather capability of synthetic aperture radars on ERS-1/2, Envisat and Radarsat-1 along with many available high spatial resolution optical sensors from several space agencies.[3]

Graßl (2006) pointed out, however, that many nations do not yet have the requisite expertise, hardware, and software needed to analyse wetlands using remote sensing. The physical diversity of wetlands requires that earth-observing satellite systems acquire data in cloudy as well as cloud-free conditions, help distinguish vegetation types by stature and/or species in both dry and wet conditions, and offer repeated observations in order to characterize the dynamic changes inherent to hydrologically dominated systems. Given these different requirements, data from multiple satellite platforms and instruments must be employed.

High spatial resolution satellite and aerial data hold much promise for analysing wetlands. Data from the SPOT sensors launched and managed by Centre National d'Etudes Spatiales (CNES) provide panchromatic imagery of approximately 1-5 m resolution. Commercial EO data, such as from Quickbird and Orbview-3, offer panchromatic data with a nominal pixel resolution of approximately 1 metre. Aerial surveys also offer data at this resolution. In many cases, data acquired from aircraft platforms may be available, in which case many types of sensors may be considered. For example, hyperspectral optical imagery, light detecion and ranging (lidar), forward-looking infrared (flir), and side-looking airborne radar (SLAR) may be available to wetlands researchers via aerial platforms. However, because these types of data are both expensive and not globally available, they may not be practical for national-level assessments of freshwater ecosystems. The resolution limit of data available to government agencies and contractors at an affordable price is approximately 30 m.

Mapping freshwater systems and deriving biological indicators of species composition or ecosystem condition are conducted collaboratively and in parallel. The products of each set of analyses may be statistically related. Taken alone, however, operational wetland indicators via remote sensing are somewhat limited.

The objective of this chapter is to describe how freshwater systems can be delineated using moderate resolution remote sensing and to suggest ways to incorporate biophysical assessments into monitoring efforts. Static data sets provide baseline boundary information for identifying rivers, inland water bodies, and watersheds. Because wetlands are inherently dynamic due to intra-annual fluctuation of water inputs and outflows, time-series methods are used to characterize that hydrologic variability. The most

2 Articles 1 and 2 of Ramsar Convention, http://www.ramsar.org/about/about_infopack_1e.htm

3 Interview cited on ESA web site (http://www.esa.int/esaEO/SEME290CYTE_index_0.html); accessed November 7, 2006.

rapid advances in remote sensing of wetlands coincide with direct collaboration between field scientists and remote sensing practitioners, especially when developing indicators of ecosystem integrity. In some cases, physical and biological assessments have been repeated through time, thus providing insight into the feasibility of operationally monitoring wetlands. These three themes (delineating wetlands globally using static representations, characterizing variability in the physical makeup of these systems, and collaboration between biodiversity and remote sensing scientists) present avenues and opportunities for linking wetland biodiversity to remotely sensed metrics.

6.2 Delineating Extent

6.2.1 Global datasets

Currently, there are two global databases of inland waters. The freely available Surface Water Body Database[4] (Slater et al. 2006) provides boundaries for large water bodies globally constructed using elevation data from the Shuttle Radar Topography Mission (SRTM) in combination with optical imagery from Landsat. The Global Lakes and Wetlands Database (Lehner and Döll 2004) contains data at three coordinated levels on 1) large lakes and reservoirs, 2) smaller water bodies, and 3) wetlands. The input data include remote sensing products such as land cover (Birkett and Mason 1995; Loveland et al. 2000). High-resolution mapping has been carried out for a small number of countries or regions, but the lack of a common classification system has hindered integration of these results with other continental or global-scale datasets.

Delineation and classification of vegetation from space have been demonstrated for a variety of wetland types (Atlantis Scientific 2002). However, several geographical features conspire against the operational use of EO satellites to map and monitor aquatic systems on a global basis. For one, despite the fact that water covers most of the planet, inland waters are sparsely distributed. Total global inland water area is between 8 and 10 million square kilometres, or 6.2-7.6 percent of total land area. Lakes and reservoirs cover much of about 2.7 million square kilometres, or 2 percent of global land area. Freshwater marshes and floodplains cover about 2 percent of Earth's land. The vast majority of wetlands are small. Half are less than about 200 ha, and about 90 percent are probably smaller than a 15 km x 15 km area (Atlantis Scientific 2002). The size of aquatic ecosystems spans 12 orders of magnitude, from spring seeps on the order of 1 m^2 (10^{-6} km^2) to the Caspian Sea, whose area is 3.7 x 10^5 km^2. Wetlands that had been listed with the Ramsar Convention by 2002 ranged in size from 1 ha to 7 x 10^6 ha (Atlantis Scientific 2002). Delineating wetland extent therefore requires data at all extents and resolutions as well as a diverse set of methods aimed at extracting relevant ecosystem parameters.

6.2.2 Regional or national scale

The task of using remote sensing to inventory inland waters is non-trivial, but there are many Earth observation capabilities available that can be exploited more fully to assess wetlands (Melack 2004; Mertes et al. 2004). The following sections describe ways of delineating the extent of inland waters and wetlands. The first examples address those below detection limits of data commonly available through EO satellite platforms while the latter examples address large inundated areas or open water bodies that may be studied using EO satellites whose data are affordable to governments around the world.

4 http://www2.jpl.nasa.gov/srtm/

6.2.2.1 Inland waters below detection limits

Most smaller rivers are not directly detectable using data at or below the 30-m resolution threshold considered a practical limit for national assessments. Often, analysts turn to watershed analysis within geographic information systems (GIS) software. These methods use digital elevation model (DEM) data to infer the direction that water would flow if travelling overland and downhill from any point in a landscape (O'Callahan and Mark 1984). Once flow direction information has been extracted, it is possible to infer the total number of cells, and hence area, above every cell in a DEM. The GIS database may further include watershed and river attributes such as forested area, land use, river discharge at measured locations, resident species, important features such as dams, water withdrawal points, discharge points, or other information pertinent to hydrology or biodiversity of wetlands (Hutchinson 1989). These GIS methods provide a means for tracking physical and biological conditions in rivers and watersheds (See Case Study 6.1).

HydroSHEDS (**H**ydrological data and maps based on **SH**uttle **E**levation **D**erivatives at multiple **S**cales) represents waterbodies, waterways, watersheds, and surface hydrology on a near-global basis and at multiple resolutions (Lehner et al. 2006). The data were built from NASA's SRTM (NASA 2005) data, which describe surface elevations for Earth's land area lying between +/- 57 degrees latitude. HydroSHEDS data may be downloaded free of charge (http://hydrosheds.cr.usgs.gov/). The goal of developing this database was to generate key data layers to support watershed analyses, hydrologic modelling, and freshwater conservation planning at previously inaccessible quality, resolution, and extent. The seamless coverage of HydroSHEDS makes this dataset useful for continental analyses because it eliminates the need to blend multiple data sources.

Case Study 6.1: Stream and Watershed Databases for Large Regions: Construction and Applications

Watershed boundary and river channel identification within a GIS can help delineate and describe river ecosystems, These methods are: 1) watershed classification based on watershed and stream morphometry, 2) hillslope-derived sediment modelling, and 3) relating watershed characteristics with biota in receiving waters (Gardiner 2002).

The study area was an 8600 km^2 region in western North Carolina (Figure 6.1) that included four watersheds: Little Tennessee, Tuckaseegee, Pigeon, and French Broad. The backwater reaches of Lake Fontana define the watershed outlets for the Little Tennessee and Tuckaseegee River watersheds in this study. The North Carolina border with Tennessee defines the northern extent of the Pigeon and French Broad study areas. For every stream in this study area, watershed boundaries and river networks were extracted and defined. Road density, percent forested area in 1970, and percent forested area in 1993 were each measured above sampling locations using GIS analyses for each watershed between 10 and 40 km^2 and with outlets between 550 and 720 m in elevation. Those data were submitted to cluster analysis (statistical classification methodology) to identify four distinct classes of watersheds: Undisturbed, Rural, Suburban, and Urban (Figure 6.2). This classification scheme allowed stream ecologists to hypothesize where streams with similar conditions might be found within a large region. The watershed database provided focal study areas for a sediment model based on the Revised Universal Soil Loss Equation (Renard 1997). Land use and local slope each influence the amount of soil loss within a given cell, and each cell's soil loss estimate was accumulated in the down-slope direction until it reached the stream channel.

A sediment transport capacity function was used to limit the allowable mass of sediment moving through a given cell (Moore and Wilson 1992). This model proved effective at estimating annual sediment flux from entire watersheds (Figure 6.3). Further, these measures of sediment loading helped to predict the proportion of endemic fishes found within samples throughout the study area (see Scott and Helfman 2001).

Watershed boundaries and river network data provided the framework for watershed classification and evaluation of land use effects on stream ecosystems across a large region. By examining the broad landscape, water resource professionals will increase their understanding of land use effects on water quality and ecological integrity.

FIGURE 6.1 Study area, including four watersheds, in western North Carolina.

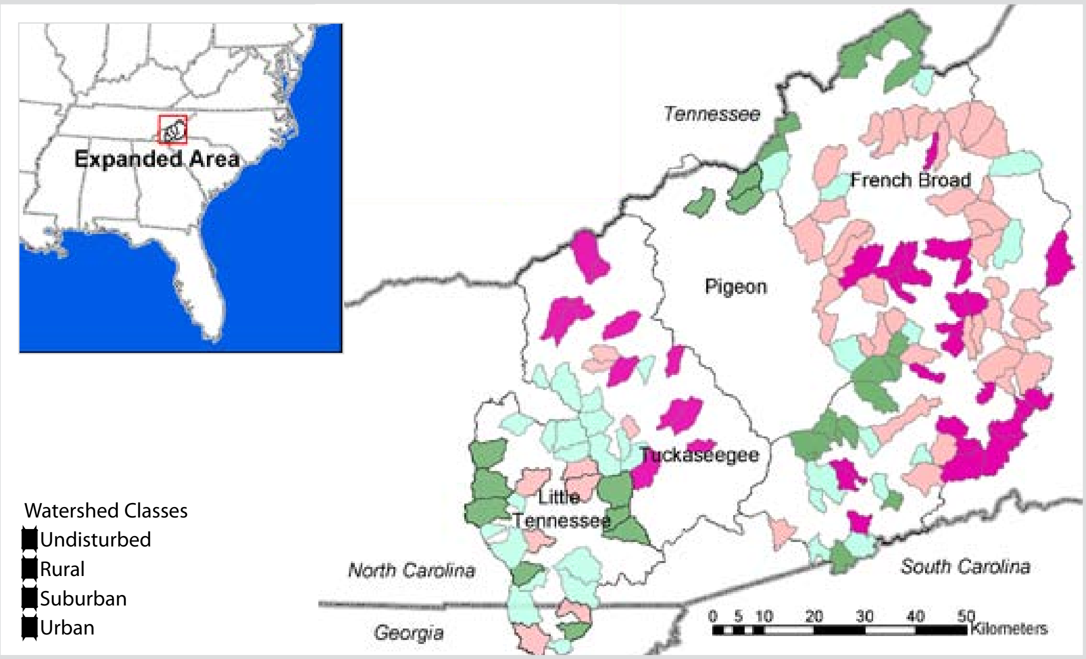


FIGURE 6.2 Watershed classification.

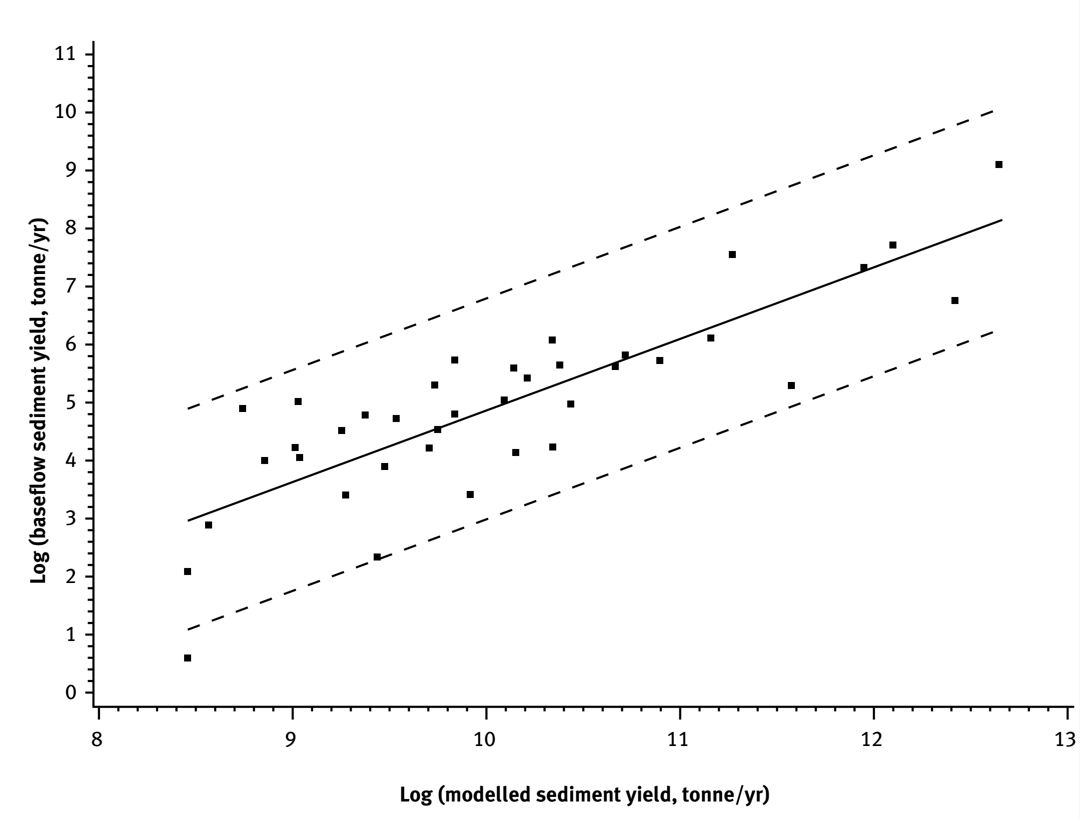


FIGURE 6.3 Modeled sediment yields were good predictors of calculated sediment yield. Regression estimates are shown with a sold line; 95 percent confidence intervals are shown with dotted lines.

FIGURE 6.4 True colour Landsat 7 ETM+ images of Hamoun Lake, bordering Iran and Afghanistan. Source: http://earthobservatory.nasa.gov/Newsroom/NasaNews/2004/2004082717537.html

6.2.2.2 Large inundated areas

Large areas that are inundated may be directly mapped using remote sensing. A simple means of evaluating the areal extent of water is to analyse near infrared reflectance in a passive optical image because water absorbs most infrared energy, generating strong contrast with surrounding landscape features that reflect infrared wavelengths (Figure 6.4). While rapid, deriving boundaries for inundated areas requires careful editing to ensure good results. Passive optical imagery is neither effective for delineating water beneath a closed canopy nor in cloudy conditions that are perennial throughout much of the tropics.

The limitations of passive optical imagery have promoted radio detection and ranging (radar) technology as a rapid means of discerning open water since the wavelengths used are long enough to penetrate clouds, haze, and vegetation. Radar also provides unique information about surface texture and reflective properties. Radar can effectively discriminate open water, inundated vegetation, and vegetation on dry land. Though radar data analysis expertise is not as common as optical remote sensing techniques, radar is indispensible to wetland delineation and monitoring. A challenge of analysing radar data is how to properly interpret single-, double-, and multiple-return signals received at the sensor. Direct collaboration between vegetation scientists and remote sensing specialists brings both perspectives to the interpretation process. Working collaboratively with experts familiar with vegetation present on the ground at Mer Bleue, Atlantis Scientific (2002) used a Van Zyl (1989) classification algorithm to attribute single- vs. multiple-return signals to distinct vegetation life forms, such as herbaceous, emergent, shrub, and tree.

Pilot studies conducted by the Treaty Enforcement Services using Earth Observation (TESEO) programme of the European Space Agency (Atlantis Scientific 2002) demonstrated the joint capabilities of both passive optical and active radar remote sensing for delineating and identifying wetland vegetation and other features at three Ramsar sites: Mer Bleue, Canada; Doñana, Spain; and Djoudj, Senegal. Their study of the Mer Bleue wetland in Ottowa, Canada utilized Landsat 7 ETM+ data as well as multi-date, multi-polarization C-band synthetic aperture radar data from both Envisat's ASAR sensor and Radarsat-2. Landsat data were used to map several vegetation classes. Radar data provided locations of tree stems emerging from inundated areas. The optical, Landsat data helped distinguish species associations, which were themselves identified through collaboration between remote sensing professionals and vegetation scientists. Radar data provided direct evidence for the location and extent of inundated areas and emergent vegetation.

The work begun by TESEO has continued, now under the auspices of GlobWetland, which itself is funded by the European Space Agency to study 17 sites around the world. Methods implemented by GlobWetland build on a body of knowledge pioneered by TESEO at Ramsar sites, but a separate effort in the Amazon (Melack 2004) provided concordant recommendations. Each of these research efforts concurs that multiple polarizations[5] of radar data are essential to differentiate vegetation types and inundated vs. non-inundated forests. Given the utility, availability, and familiarity of optical remote sensing data (see Case Study 6.2) and the discriminatory power of radar to detect surface conditions below tree canopies as well as clouds, it is clear that multiple data types and sources must be used to effectively map wetland vegetation (Atlantis Scientific 2002).

Case Study 6.2: Remote monitoring of biodiversity at Doñana National Park

Author: Ricardo Díaz-Delgado Hernández

Established in 1968, Doñana National Park (537 km^2) is both a Biosphere Reserve and a Ramsar Site. It contains the largest wetland in Europe, a complex matrix of marshlands (273 km^2), phreatic lagoons, a 25 km-long dune ecosystem, and representative Mediterranean terrestrial plant communities (Figures 6.5a and 6.5b). Conservation objectives include the preservation of critically endangered species (Iberian Lynx, Imperial Eagle), waterfowl, and representative Mediterranean wetlands and terrestrial ecosystems. Doñana is both a critical stopover site for Palearctic birds migrating to Africa and an important overwintering site for waterfowl.

Remote sensing has been used as a monitoring tool for Doñana ecosystems since 2002; images are being used to monitor:

- Shoreline and dune system dynamics
- Sedimentation processes in the marshland
- Terrestrial and marshland plant community changes
- Temporal patterns of marsh inundation and water turbidity
- Monitoring progress with ecological restoration of transformed marsh areas
- Land use and land cover changes in the vicinity of Doñana National Park.

A time series of co-registered and calibrated Landsat satellites images (MSS, TM and ETM+), regularly updated through a Landsat-5 TM subscription and many Landsat 7 ETM+ SLC-off scenes, provides a record spanning over 30 years (1975-2007).

Semi-automated image texture and brightness analyses of ETM+ middle infrared (band 7) data distinguish sand from other land cover (such as water and pine forests), thus providing dune and shoreline boundaries. By comparing scenes from the last 23 years, we have observed that the most active dunes have advanced approximately 6 m/yr. In the south of the Park, the beach has advanced up to 18 m/yr, though the increase is not evenly distributed across beach front areas (Figure 6.5c). Sedimentation rates have increased in the watershed of the marsh in the last decade. Marsh restoration initiatives aim to reduce this trend.

5 For a given wavelength, pulses may be transmitted with horizontal (H) or vertical (V) polarization. Return pulses may be recorded in either H- or V-mode, as well. Each radar instrument is characterized by its wavelength (e.g., X, C, L, or P from shorter to longer wavelength) as well as the outgoing and return pulse phases, which are designated as HH for horizontal-horizontal, HV for horizontal-vertical, and so forth. Shorter wavelength (C-band) radar data are useful for detecting and mapping floating macrophytes, emergent vegetation including grasses and wetland rice paddies, and even leaf area. Scattered Melaleuca forests in Australia and low-density Varzea forests in Amazonia may be mapped using C-band data (Melack 2004). This frequency is less effective under thick canopies or when stem density increases. Longer-wavelength (L-band) data were better suited to penetrate dense stands and closed canopies typical of mature wetland forests with high woody biomass. The most dense forests may require use of P-band SAR data, but currently P-band SAR data are only available on aerial platforms. Both HH and HV polarizations were needed to map flooded vs. non-flooded forests and woody vs. non-woody vegetation in Amazonia (Melack 2004).

In recent decades, land cover conversion and overgrazing have changed inundation patterns and thus susceptibility to drought. We use supervised classification to map both shrublands and marshland vegetation. Field observations from sampling plots, established as training areas where forest and shrubland stand structure are measured on the ground, have corroborated seedling mortality assessments following recent droughts. Episodic droughts require joint monitoring via remote sensing and ground-based observations.

Research focused on discriminating inundation levels, turbidity, and depth using multi- and hyperspectral imagery has enabled us to reconstruct a historical profile of the inundation regime of Doñana marshes. Hydroperiod (the time during which a wetland is covered with water) values for every pixel have been calculated from inundation maps generated through simple thresholding of TM and ETM+ bands 5 (MSS band 4); this near infrared band is the best indicator of water level in shallow wetlands (Díaz-Delgado et al. 2006a). Hydroperiod helps researchers develop a greater understanding of plant presence, abundance, and inundation trends that may be human- or naturally induced (Díaz-Delgado et al. 2006b; Figure 6.6).

A large restoration project called "Doñana 2005" was initiated after a toxic spill from a local mine in April 1998 that severely compromised water quantity and quality entering Doñana marshes (Pain et al. 1998). Multispectral images together with airborne campaigns of the Airborne Hyperspectral Scanner (AHS) tracked the effectiveness of restoration efforts that promoted the return of natural species assemblages and the recovery of natural processes.

All information generated from remote sensing is accessible through the worldwide web, allowing easy access and use of monitoring results. Two websites are available to visualize and download data:

- http://www-rbd.ebd.csic.es/Seguimiento/seguimiento.htm: results for all monitoring topics and methodological protocols.
- http://mercurio.ebd.csic.es/seguimiento/: web map server showing the location of all the ground sampling plots and providing results in a spatial context.

The frequent revisit time of Landsat (16 days for either ETM+ or TM but only 7 days using both in combination) has proved sufficient for our purposes. The 30m pixels of Landsat have been sufficient for landscape monitoring at Doñana. However, the spectral sensitivity of Landsat is insufficient for monitoring species assemblages. To discern dominant plant abundance among 8 species of shrub, we are using hyperspectral airborne sensors and Spectral Unmixing Analysis (Jiménez et al. 2007).

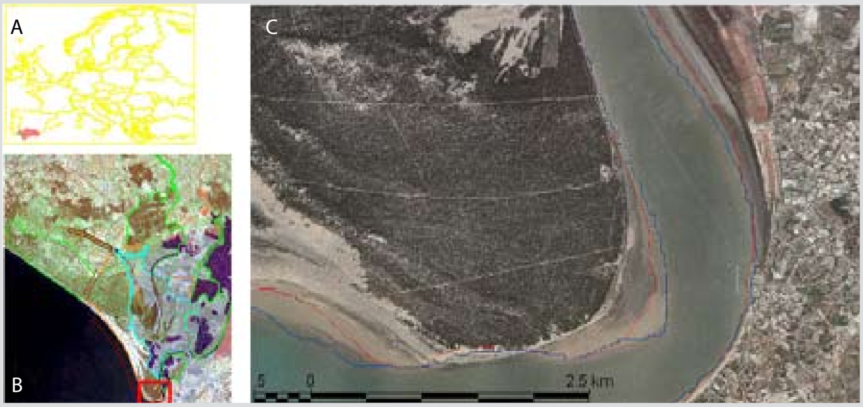


FIGURE 6.5A Location of Doñana (green polygon) inside the autonomous region of Andalucia (red polygon) in southern Spain; B Boundary of Doñana National Park (orange line), marshland ecosystems (blue line), and Doñana Natural Park (green line); C Zoom of red square in b) displaying an overlay with transparency of 1956 (b/w) and 1998 (colour) aerial photos of the mouth of Guadalquivir River showing the progradation process (beach creation) at this area. Red and blue lines indicate shoreline in 1984 and in 2004 respectively as detected through Landsat TM 7 segmentation.

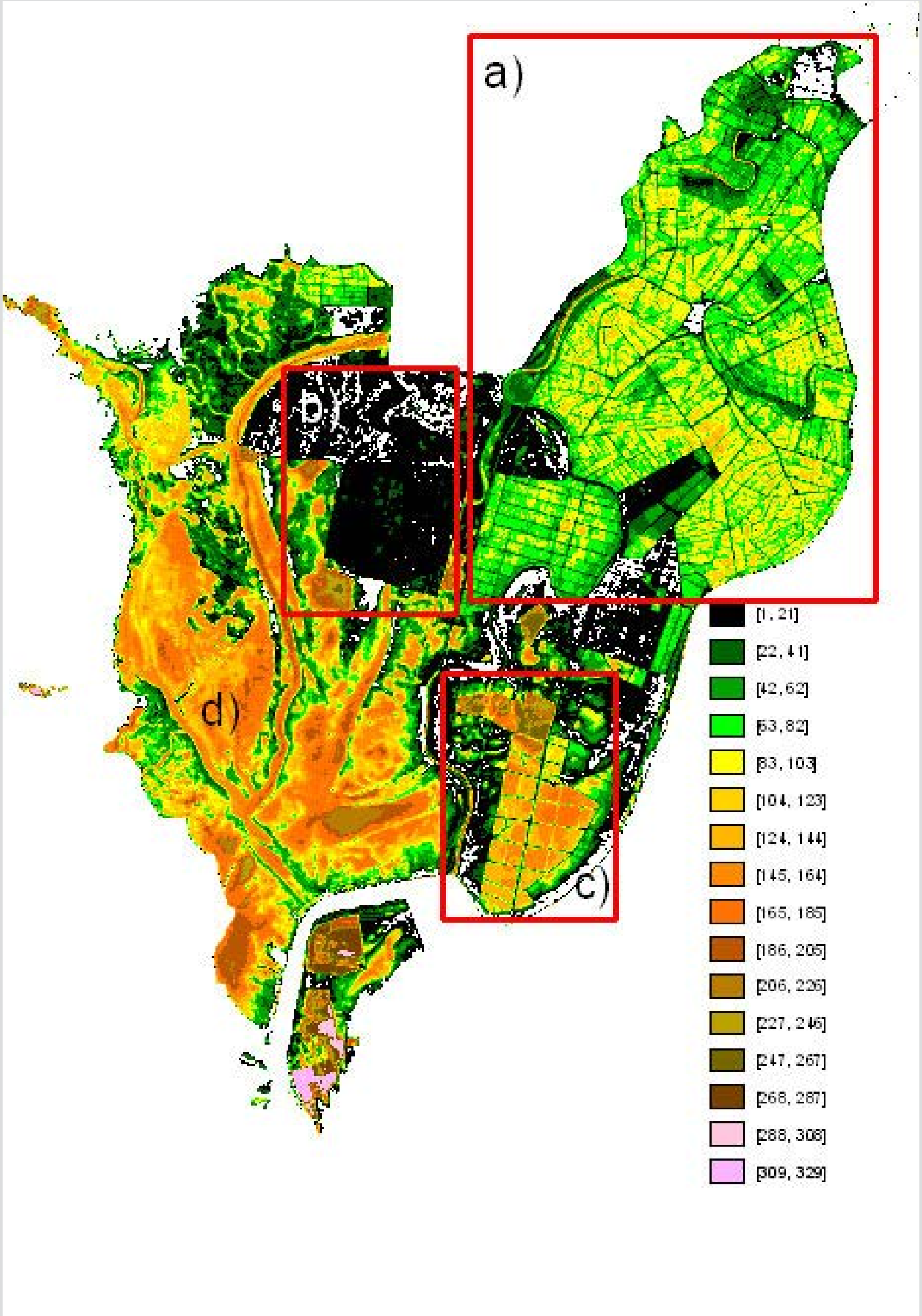


FIGURE 6.6 Average hydroperiod (days) of Doñana marshland estimated from annual hydroperiods of the period 1975-2005. a) Rice fields, b) desiccated marsh, c) fisheries, and d) natural marshland.

6.2.2.3 Mapping variability of water levels and extent

Data acquired at high- and low-water are needed to accurately map wetland extent because these ecosystems are defined by water level fluctuation and function differently at different water levels (see Case Study 6.2). The acquisition time of archived data may be compared to the best-known stage information for a given area in order to choose imagery that will be of most use for characterizing high- and low-water regimes of the targeted ecosystem. For upland wetlands, antecedent soil moisture and precipitation affect river discharge, wetland extent, and surface water levels and therefore influence the optimal date for acquiring imagery. The situation is more complex for seasonally inundated systems that receive water input from rivers because river flood stage and peak flow are influenced by upstream, catchment-wide hydrological factors that delay peak discharge relative to peak precipitation events. Temperate rivers reach bank full stage with a recurrence interval of between 1.5 and 2.5 years, suggesting that optimal data for analysis might appropriately come from different years in order to capture both low- and high-water events within the data record for a site. Mapping the high- and low-water stages of rivers with active floodplain systems, such as the Amazon, is important since the function of these systems is defined relative to that variation in water level and extent.

The behavior, function, and aerial extent of wetlands changes through time, so characterizing changes in habitat quality requires a thorough understanding of natural variability. Water and nutrients are transported from headwaters to downstream river ecosystems, but there is a bidirectional interaction of rivers with active floodplains. Nutrient flux from floodplains into river food webs is an important linkage between rivers and the floodplain habitat associated with them. When researchers first mapped and compared the extent of floodplain inundation at high- and low-water levels, they surmised that the mass of carbon emitted from rivers in the form of CO_2 during high water stages throughout the year was comparable in magnitude to the amount of carbon transported down river (see Melack 2004). Thus, accurate mapping at high- and low-water levels has led to significant new insights into the structure and function of aquatic systems.

Recent remote sensing efforts have demonstrated how to map floodplain forests using a variety of satellite sensors and data available at multiple resolutions. Hamilton and colleagues (2007) used remotely sensed data in combination with HydroSHEDS river network data to characterize wetlands in floodplains of the Madre de Dios River. They mapped floodplains, standing water, and vegetation associated with unique geomorphic settings in this flood-dominated ecosystem (see Figure 6.7). This research employed object-oriented, contextual classification, a set of techniques that utilizes the spatial setting of landscape features to help identify and classify imagery. Image data included Landsat 7 ETM+ data, elevation profiles from NASA's SRTM, and JERS-1 L-band radar scatterometer mosaics. The Landsat and SRTM data were stacked and subsequently divided into clusters of pixels. Landsat data and JERS-1 mosaics were used to classify image clusters describing small features, such as individual meander bends. At a coarse scale, SRTM elevation data successfully distinguished uplands from floodplains. Their hierarchical, multi-scale analysis combined the unique capabilities of optical and radar data to extract vegetation classes and geomorphic types. Both vegetation and geomorphic features were further related to hydroperiod, with water and vegetation features closer to the river showing chemical and hydrologic influences from the river while features set back into the floodplain were more influenced by groundwater than by the river. Those biogeochemical classifications were determined and verified through ground surveys and laboratory analyses. This study demonstrates the capabilities of modern remote sensing image processing when applied to DEM, optical, and radar data. *In situ* data enhanced the authors' ability to delineate ecologically relevant features of a flood-pulse dominated landscape.

If a water body is between 0.5 and 1.0 km in width or 100-300 km^2 in area, satellite-based radar altimeters may be used to monitor their water levels (Mertes et al. 2004). That size restriction eliminates

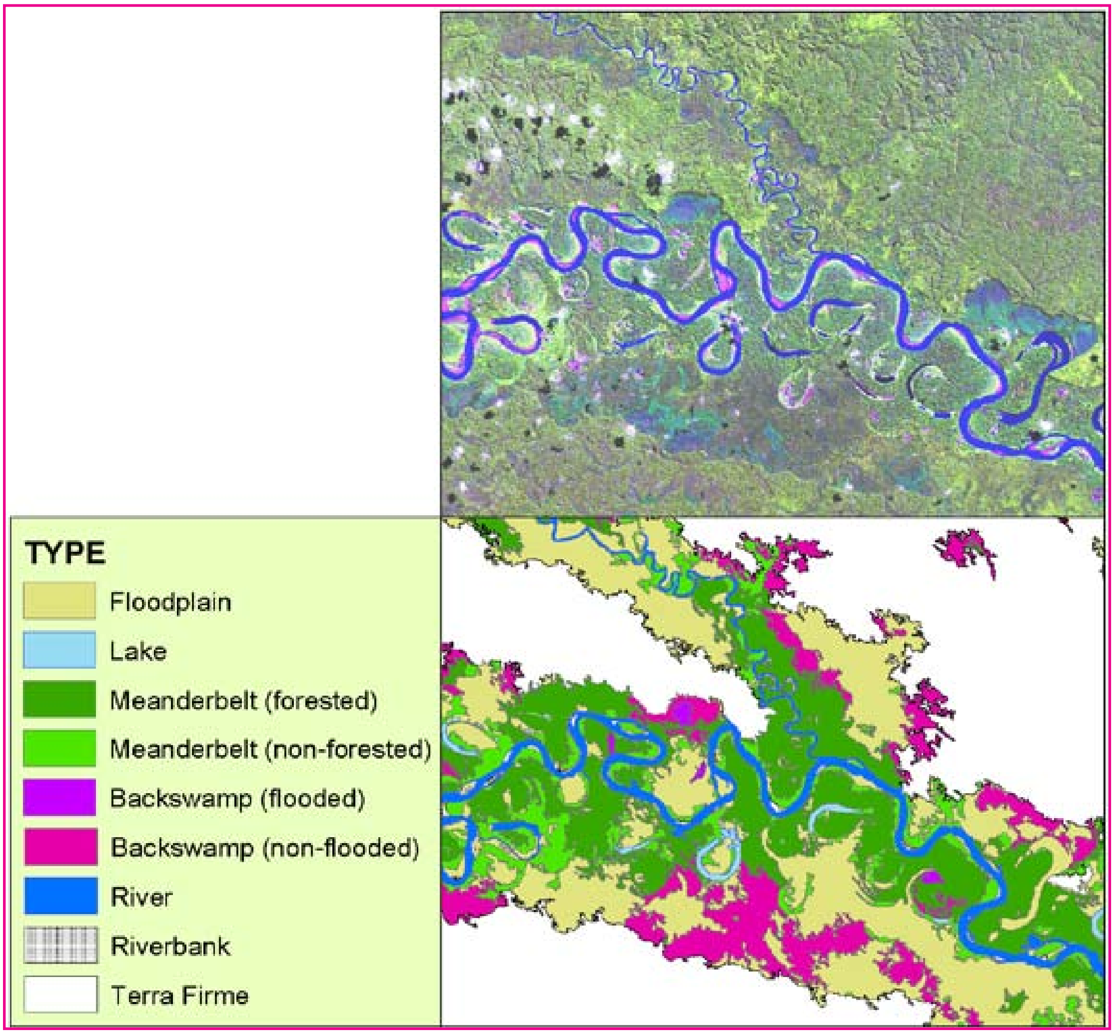


FIGURE 6.7 Floodplain vegetation in the Madre de Dios River System, Brazil (Hamilton et al. 2007).

about 90 percent of Ramsar sites (Atlantis Scientific 2002), but for large, open water bodies, this technology has proven highly valuable. It is being used operationally by the United States Department of Agriculture (USDA) Foreign Agriculture Service (FAS) to monitor water supply throughout the world (Figure 6.8)[6].

The 2002 TESEO study (Atlantis Scientific 2002) emphasized that C-SAR data were effective in identifying the varying extent of wetlands through wet and dry seasons. Inundated areas with no vegetation scattered radar signals but did not reflect them back to the sensor. Thus, water areas appeared dark in resultant imagery. This principle underlies the use of radar for delineating the extent of open water. Where emergent vegetation was present, some backscatter was evident. This physical property allows analysts to clearly identify inundated vegetation. Employing these principles, the TESEO study mapped seasonal wetland variability. In spring, there were wide expanses of open water and flooded vegetation whose area decreased through the dry summer and early fall; in October 1995, wetland extent increased once again. This ability to monitor the seasonal changes in extent of open water and flooded vegetation

6 http://www.pecad.fas.usda.gov/cropexplorer/global_reservoir/

is useful for characterizing wetland responses to varying hydrologic periods.

6.2.2.4 Coupling biological and physical assessments

To evaluate in situ biological and physical properties of river ecosystems, researchers often use "multimetric" indicators, statistical descriptions that simultaneously describe a site's species and local habitat relative to undisturbed sites with similar landscape settings. Multimetric indicators are derived empirically from a set of sites or through time, for example from density or relative proportion of taxa collected at a site or group of sites. The categories and point assignments used to derive multimetric scoring systems must be calibrated to the fishes, macroinvertebrates, or microbes found in streams and rivers within a bioregion, so this work is conducted by a biologist with the requisite expertise in regional fauna and flora. Fish and invertebrate ecologists have the most experience using multimetrics to describe and categorize ecosystem health in rivers and streams, but taxonomists and ecologists are studying how to develop indicators of stream health that focus on the microbes found at a stream sampling site. Multimetric scores can be compared statistically to land use data derived from remote sensing and extracted on a watershed basis using GIS software. This statistical approach guides inferences about the effect of watershed practices on streams or rivers. This procedure is widely practiced but should be conducted only through direct collaboration among experts in GIS, remote sensing, and freshwater biology.

Large rivers, lakes, reservoirs, and estuaries provide sufficient surface area for direct detection by space-based sensors of water and water quality parameters that are sensitive to catchment-wide land use changes as well as internal physical, chemical, and biological dynamics. Direct detection and satellite-based modelling of primary productivity in large lakes has been feasible for several decades (Dekker and Seyhan 1988, Dekker et al. 1991, 1992a, 1992b, Dekker and Peters 1993). Two low-resolution sensors, MODIS and SeaWifs, have operational chlorophyll detection algorithms that exploit the high reflectivity of phytoplankton in infrared wavelengths. Hyperspectral technologies have also been used to study primary productivity of inland waters (Hoogenboom et al. 1998), although these studies focus on very small areas and use data not available on a global basis. Optical data are also used to estimate suspended solids concentrations in large water bodies (Dekker et al. 2001).

6.3 Changes in Habitat and Ecosystem Quality

Change and variability are inherent to the structure and functioning of wetlands. Just as one may assess the natural variability of water extent, exogenous inputs, and biota within wetlands, it is possible to measure long-term trends and changes to wetlands using the same or similar methods. Some changes to wetlands can be evaluated somewhat directly, for example the influence of land cover change on the timing and delivery of water and suspended constituents to rivers, or the effect of global warming on boreal wetlands. This section focuses on watershed-based, optical, and radar-based monitoring of wetlands that are undergoing anthropogenic change.

6.3.1 Rivers and watersheds

Land cover change upstream of receiving waters alters the hydrologic, nutrient, and physical templates of those ecosystems. When forested catchments are clear-cut in temperate forest ecosystems, recovery of some parameters, such as nutrient retention and turnover, requires up to several years to re-establish pre-disturbance regimes. Other physical characteristics require decades for recovery. For example, sediment delivered to rivers and streams following a major disturbance, such as watershed-wide

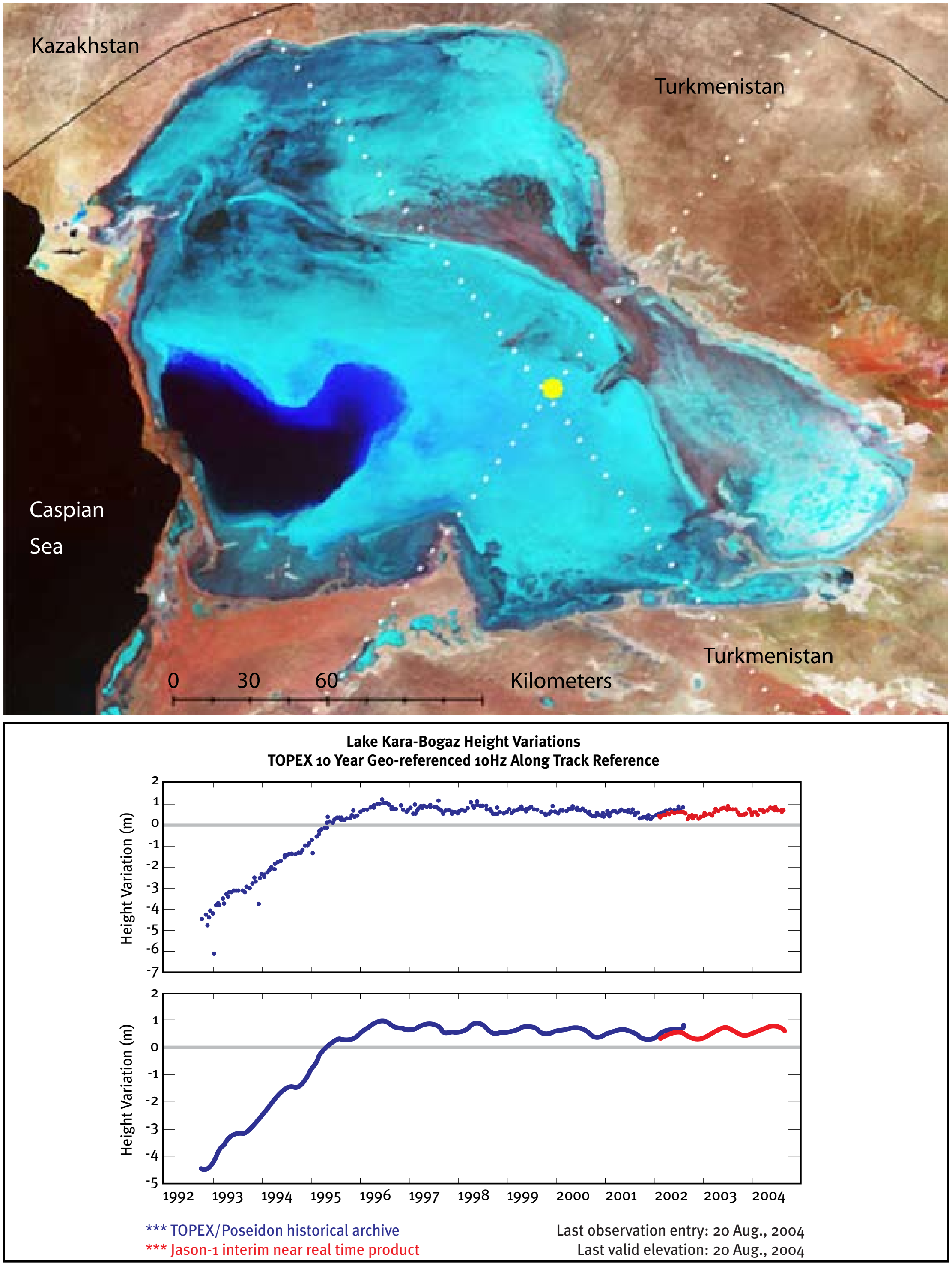


FIGURE 6.8 Satellite tracks for Jason-1 satellite passing over Lake Kara Bogaz, Turkmenistan, overlain on Landsat 5 TM image (top). Graphs below depict lake elevation from both TOPEX/Poseidon (blue) and Jason-1 (credit: USDA global reservoir database). The steady increase from 1992 through 1995 demonstrates the rising water elevation following a breach of the barrier with the Caspian Sea, which led to the formation of this water body.

clear-cutting, may require infrequent, episodic torrential rain events in order to generate sufficient hydrologic power to redistribute large quantities of sediment downstream. Once vegetation recovers, the legacy of historic deforestation events can therefore have a very long-lasting impact on the habitat template of stream ecosystems.

In addition to characterizing ongoing changes to streams through monitoring catchment-wide land cover change, understanding wetlands requires that one document and understand the historic changes that have occurred in that ecosystem's watershed. The methods for characterizing hydrologic processes, and therefore the integrity of flowing water ecosystems, hinge on accurate delineation of land cover and historic land cover throughout a watershed. Specific techniques for analysing land cover are addressed throughout this volume. Given adequate land cover data for key dates, for example before and after major land use changes, it is possible to quantitatively estimate changes to hydrologic regimes or loadings of constituents that alter habitat quality, such as sediment, nutrients, and trace elements. As with the assessments described previously (e.g., Case Study 6.1), the relationships between watershed conditions and river discharge, loadings, and concomitant habitat quality must be calibrated based on knowledge of regional conditions.

Spatial data describing regional climate patterns, physiography, land cover, and land use lend insight into how to manage watersheds. Conservation planners prioritize their effort using the best available data describing a region of interest. Often, data describing biodiversity are absent, so planning must move forward in the absence of biological information using surrogate measures such as climate information. Planners and researchers from WWF-US, Michigan State University, Woods Hole Research Center, and WWF-Peru recently prioritized conservation recommendations for a 160,000 km^2 headwater region of the Madre de Dios and Orthon rivers in Peru (Thieme et al. 2007). Each river is a tributary of the Amazon River, and the study area as a whole is within the southwestern Amazonian Moist Forests ecoregion of the Global 200 priority regions identified by Olson and Dinerstein (1998). The work used GIS-based analyses of terrain, vegetation, and existing protected areas to recommend areas for conservation attention. The study's authors hope the work will prevent problems arising from road building and other land-clearing activities that are likely to accompany oil and gas exploration in the region. Activities such as these will remove vegetation and expose soil, thereby increasing sediment delivery to waterways through erosion and transport of disturbed soil. Sedimentation is among the most common processes that degrade river ecosystems. GIS data describing watershed boundaries, stream channels, and watershed morphometry provided requisite data for evaluating potential discharge along stream segments, percentage of watershed area found within the Andes, and connectedness of river segments among protected areas that have already been identified. Watershed-based analyses, such as those conducted in the Madre de Dios River basin, are an essential component of evaluating the potential influence of land use decisions on wetlands.

6.3.2 Ecosystem structure and function

Remote sensing analyses complement campaigns focused on the structure and function of wetland ecosystems. For example, due to changes in freeze-thaw cycles and permafrost conditions stemming from global warming, there is increasing attention and interest in greenhouse gas emissions from boreal forests. Approximately 25 percent of the carbon that is bound within terrestrial ecosystems is likely found in high-latitude peat lands (Hess and Melack 1994). When they dry out, peat lands respire CO_2 and CH_4 into the atmosphere, so monitoring inundation in these areas is important for quantifying greenhouse gas emissions from peat lands. In boreal Siberia and eastern Canada, Gorham (1991) posited that satellite data may be used to monitor the declining area of open water as an indicator of global warming effects on peat land ecosystems, but that effort also requires contribution from biogeochemists with expertise

FIGURE 6.9 Seasonally melted, freeze-thaw lakes (yellow outlines) in northeastern Siberia depicted in a Landsat 7 image. Methane release from these lakes is greater than previously realized.

in quantifying and evaluating outgassing. Conversely, biogeochemists recently estimated that methane emissions from seasonally melted lakes in permafrost regions of Siberia may contribute about twice as much CH_4 to the atmosphere as previously thought (Walter et al. 2006). Their estimates were based on field-collected samples from a handful of lakes, and results were extrapolated based on estimates using GIS and remote sensing (Figure 6.9). Kimball and colleagues (2006) have used microwave data to show that seasonality has changed in recent decades, with warm temperatures arriving earlier in the year and cold temperatures arriving later.

The examples provided demonstrate the feasibility of using remote sensing indicators to measure natural variability in wetland extent. Coordinated field campaigns and remote sensing research can yield statistically rigorous relationships between remote sensing indicators and biophysical characteristics of wetland ecosystems. For rivers below the detection limits of remote sensing, watershed modelling within GIS software utilizes remotely sensed land cover information to derive hydrologic and suspended loading information that can be used to infer habitat quality parameters. Larger water bodies may be directly mapped, both in terms of aerial extent and water elevation.

6.4 Summary of the Use of Satellite Data for Operational Monitoring

The most promising avenues for developing remote sensing indicators for riverine ecosystems that are below the direct detection limits of satellites are: 1) watershed classification, which incorporates GIS data and remote sensing measures of land cover and land use, and 2) developing statistical relationships between biota and watershed or river reach descriptions stored within a GIS and derived from both GIS data and remote sensing. Remotely sensed observations may be used effectively to delineate wetland ecosystems; data interpretation requires expertise in ecosystem assessment. Ecologists familiar with a given site can greatly enhance the ability of remote sensing analysts to extract meaningful map products from satellite-derived data.

Mapping wetlands around the world has previously been conducted at low resolution; within 1-

degree cells, inundated area was estimated to provide some idea of greenhouse gas emissions from five types of wetlands (Matthews and Fung 1987). Mapping at higher resolution will require both optical and radar sensor systems. Countries seeking to delineate freshwater systems rely on data available through government agencies and government purchase agreements. The one- to two-day repeat interval offered by low-resolution optical sensors, such as MERIS or MODIS, offers imaging data of particular use in areas not obstructed by clouds and for large water bodies. The medium resolution capabilities of NASA's Landsat series of instruments and CNES' SPOT instruments offer resolution between 30 m and 5 m and therefore reveal more detail about smaller water bodies and seasonally inundated areas. Canada Space Agency's synthetic aperture radar (SAR) data are an important resource for mapping wetlands globally. Radarsat-1 provided HH-polarization only, while Radarsat-2 provides both single- and dual-polarization. Radarsat-2 can provide SAR data at a resolution of up to 3 m.

A variety of researchers (see Melack 2004 and references therein) and demonstration projects (see Mer Bleue studies by Atlantis Scientific 2002) have found that C-band radar can be used to measure seasonal changes in inundation of vegetation, even for low-stature grasses and forbs. The VV polarization of C-band radar data has been shown to be sensitive to the density of rice in fields as well as natural wetland, non-woody vegetation. The longer wavelength, L-band of radar penetrates the more dense canopies of forests and therefore can distinguish flooded and non-flooded forest vegetation. C-band SAR is a promising sensor type for monitoring seasonal changes in flooded vegetation. Polarimetric C-band SAR can discriminate major classes of vegetation, such as herbaceous cover, shrubs, and forests. Radar altimetry and interferometry hold promise for measuring subtle elevation changes in peat bogs and may provide an indication of annual vegetation growth. HH polarization distinguishes inundated vegetation from dry vegetation and from water due to backscatter characteristics of each of these feature types.

6.5 Data and Other Resources

HydroSHEDS

HydroSHEDS promises near-global river drainage information at multiple resolutions (http://www.worldwildlife.org/freshwater/hydrosheds.cfm)

Surface Water Database from NASA/JPL (http://www2.jpl.nasa.gov/srtm/)

Acknowledgments

This paper was stimulated by a workshop hosted April 6, 2005 by the American Museum of Natural History's Center for Biodiversity and Conservation through support from NASA under grant NNG04GC18G. Some research cited here was funded by NSF Grant DEB96-32854 to the Office of the Vice President for Research at the University of Georgia, and NASA grant NAG5-6479 to the University of Georgia. Laura Hess provided crucial insight into the operational use of radar data. The case study for Doñana was funded by Doñana National Park administration (Spanish Ministry of Environment) through the research project "Reconstruction of bird population dynamics during the last three decades" and by the Spanish Ministry of Science and Education through the research project HYDRA (# CGL2006-02247/BOS). Doñana National Park and Natural Park provided permits for field work in protected areas with restricted access. A. Travaini, H. Le Franc, D. Paz, A. Polvorinos, and I. Román helped with field work. J.C. Gilabert, J.L. Pecharromán and P.L. Porta helped with image processing.

6.6 References

Atlantis Scientific, Inc. 2002. Treaty Enforcement Services Using Earth Observation: Wetlands Monitoring. ESRIN Contract No. 15461/01/1-LG. Final Report Submitted to ESRIN Contracts Service.

Birkett, C.M., Mason, I.M. 1995 A new global lakes database for a remote sensing program studying climatically sensitive large lakes. Journal of Great Lakes Research 21(3): 307-318.

Bustamante, J., F. Pacios, R. Diaz-Delgado, and D. Arangonés. In Press. Predictive models of turbidity and water depth in the Doñana marshes using Landsat TM and ETM+ images. Journal of Environmental Management.

Coates, D. 1995. Inland capture fisheries and enhancement: status, constraints, and prospects for food security. In, International Conference on Sustainable Contribution of Fisheries to Food Security. Kyoto, Japan: Government of Japan and FAO, Rome, Italy.

Danielsen, F., M.K. Sørensen, M.F. Olwig, V. Selvam, F. Parish, N.D. Burgess, T. Hiraishi, V.M. Karunagaran, M.S. Rasmussen, L.B. Hansen, A. Quarto, and N. Suryadiputra. 2005. The Asian Tsunami: A Protective Role for Coastal Vegetation. Science 310 (3748): 643.

Dekker, A. G., T. J. Malthus, and E. Seyhan. 1991. Quantitative Modeling of Inland Water-Quality For High-Resolution MSS Systems. IEEE Transactions on Geoscience and Remote Sensing 29:89-95.

Dekker, A. G., T. J. Malthus, M. M. Wijnen, and E. Seyhan. 1992a. The Effect of Spectral Bandwidth and Positioning on the Spectral Signature Analysis of Inland Waters. Remote Sensing of Environment 41:211-225.

Dekker, A. G., T. J. Malthus, M. M. Wijnen, and E. Seyhan. 1992b. Remote-Sensing as a Tool For Assessing Water-Quality In Loosdrecht Lakes. Hydrobiologia 233:137-159.

Dekker, A. G., and S. W. M. Peters. 1993. The Use of the Thematic Mapper for the Analysis of Eutrophic Lakes – A Case-Study in The Netherlands. International Journal of Remote Sensing 14:799-821.

Dekker, A. G., and E. Seyhan. 1988. The Remote-Sensing Loosdrecht Lakes Project. International Journal of Remote Sensing 9:1761-1773.

Dekker, A. G., R. J. Vos, and S. W. M. Peters. 2001. Comparison of remote sensing data, model results and in situ data for total suspended matter (TSM) in the southern Frisian lakes. Science of the Total Environment 268:197-214.

Díaz-Delgado, R., Bustamante, J., Aragonés, D. and Pacios, F. 2006a. Determining water body characteristics of Doñana shallow marshes through remote sensing. In Proceedings of the 2006 IEEE International Geoscience & Remote Sensing Symposium & 27th Canadian Symposium on Remote Sensing (IGARSS2006), organized by the Geoscience and Remote Sensing Society. Denver, Colorado, USA, 31 July-4 August 2006. Pages: 3662-3664.

Díaz-Delgado, R., Bustamante, J., Pacios, F. and Aragonés, D. 2006b. Hydroperiod of Doñana marshes: natural or anthropic origin of inundation regime? In Proceedings of the 1st GlobWetland Symposium, organized by ESA and Ramsar Convention. Frascatti, Italy, 19-20 October.Gardiner, E.P. 2002. Geospatial Techniques for Stream Research in the Southern Blue Ridge Mountains. Ph.D. Dissertation. University of Georgia, Athens.

Gardiner, E.P. 2002. Geospatial techniques for stream research in the southern Blue Ridge Mountains. Ph.D. Dissertation. Athens: University of Georgia

Gorham, E. 1991. Northern Peatlands – role in the carbon cycle and probable responses to climatic warming. Ecological Applications, 1, 182-195.

Hamilton, S.K., J. Kellndorfer, B. Lehner, and M. Tobler. 2007. Remote sensing of floodplain geomorphology as a surrogate for biodiversity in a tropical river system (Madre de Dios, Peru). Geomorphology.

Hess, L.L. and Melack, J.M. 1994. Mapping wetland hydrology and vegetation with synthetic aperture radar. International Journal of Ecological and Environmental Science 20:197-205.

Hoogenboom, H. J., A. G. Dekker, and I. A. Althuis. 1998. Simulation of AVIRIS sensitivity for detecting chlorophyll over coastal and inland waters. Remote Sensing of Environment 65:333-340.

Hutchinson, M.F. 1989. A new procedure for gridding elevation and stream line data with automatic removal of spurious pits. Journal of Hydrology, 106, 211-232

Jiménez, M., Díaz-Delgado, R., Vaughan, P., Fernández-Renau, A., Gutiérrez, O. and Prado, E. 2007. Airborne Hyperspectral Scanner (AHS) a priori mapping capacity for the Doñana Biological Reserve shrublands. Proceedings of the 10th International Symposium on Physical Measurements and Signatures in Remote Sensing. Organized by International Society for Photogrammetry and Remote Sensing. Davos, Switzerland, 12-14 March. page 80.

Junk, W.J., Bayley, P.B., & Sparks, R.E. 1989. The flood pulse concept in river-floodplain systems. In D.P. Dodge (Ed.), Proceedings of the International Large River Symposium. Canadian Special Publication in Fisheries and Aquatic Sciences. pp. 110-127

Kimball, J.S., McDonald, K.C., & Zhao, M. 2006. Terrestrial vegetation productivity in the western arctic observed from satellite microwave and optical remote sensing. Earth Interactions 10, 22.

Lehner, B., K. Verdin, A. Jarvis. 2006. HydroSHEDS Technical Documentation, Version 1.0. http://gisdata.usgs.net/HydroSHEDS/downloads/HydroSHEDS_TechDoc_v10.pdf

Lehner, B. and P. Döll 2004: Development and validation of a global database of lakes, reservoirs and wetlands. Journal of Hydrology 296/1-4: 1-22.

Loveland, T.R., Reed, B.C., Brown, J.F., Ohlen, D.O., Zhu, J, Yang, L., and Merchant, J.W. 2000: Development of a global land cover characteristics database and IGBP DISCover from 1-km AVHRR data. International Journal of Remote Sensing 21(6/7): 1303–1330.

Matthews, E. and I. Fung. 1987. Methane emissions from natural wetlands: Global distribution, area, and environmental characteristics of sources. Global Biogeochemical Cycles 1: 61-86.

Melack, J.M. 2004. Remote sensing of tropical wetlands in S. Ustin, editor. Manual of Remote Sensing, 3rd edition. Remote Sensing for Natural Resources Management and Environmental Monitoring. 3 ed., Vol. 4. John Wiley & Sons, New York. Pages 319-343.

Mertes, L.A.K., A.G. Dekker, G.R. Brakenridge, C.M. Birkett, G. Létourneau. 2004. Rivers and lakes in S. Ustin, editor. Remote Sensing for Natural Resources Management and Environmental Monitoring: Manual of Remote Sensing, 3 ed., Vol. 4. John Wiley & Sons, Inc. 345-400.

Moore, I.D., & Wilson, J.P. 1992. Length-slope factors for the revised universal soil loss equation: simplified method of estimation. Journal of Soil & Water Conservation 47, 423-428.

O'Callaghan, J.F., & Mark, D.M. 1984. The extraction of drainage networks from digial elevation data. Computer Vision, Graphics and Image Processing, 28, 323-344.

Olsen, D.M. and E. Dinerstein. 1998. The Global 200: a representative approach to conserving the Earth's most biologically valuable ecoregions. Conservation Biology 12: 502–515.

Pain, D.J., Sánchez, A., & Meharg, A.A. 1998. The Doñana ecological disaster: contamination of a word heritage estuarine marsh ecosystem with acidified pyrite mine waste. The Science of the Total Environment, 222, 45-54

Peterson, B. J., W. M. Wollheim, P. J. Mulholland, J. R. Webster, J. L. Meyer, J. L. Tank, E. Marti, W. B. Bowden, H. M. Valett, A. E. Hershey, W. H. McDowell, W. K. Dodds, S. K. Hamilton, S. Gregory, and D. D. Morrall. 2001. Control of Nitrogen Export from Watersheds by Headwater Streams. Science 292:86-90.

Renard, K.G. 1997. Predicting Soil Erosion by Water: A Guide to Conservation Planning with the Revised Universal Soil Loss Equation (RUSLE). USDA Agricultural Research Service Agriculture Report 703.

Ricciardi, A. and J.B. Rasmussen. 1999. Extinction rates of North American freshwater fauna. Conservation Biology 13 (5): 1220-1222.

Scott, M.C., & Helfman, G.S. 2001. Native invasions, homogenization, and the mismeasure of integrity of fish assemblages. Fisheries, 26, 6-15.

Slater, J.A., G. Garvey, C. Johnston, J. Haase, B. Heady, G. Kroenung, and J. Little. 2006. The SRTM data "finishing" process and products. Photogrammetric Engineering and Remote Sensing 72:237-247.

Thieme, M., B. Lehner, R. Abell, S.K. Hamilton, J. Kellndorfer, G. Powell, and J.C. Riveros. 2007. Freshwater conservation planning in data-poor areas: an example from a remote Amazonian basin (Madre de Dios River, Peru and Bolivia). Biological Conservation 135: 500-517.

Van Zyl, J. 1989. Unsupervised classification of scattering behavior using radar polarimetry data, IEEE Transactions on Geoscience and Remote Sensing 27(1):36-45.

Walter, K.M., S.A. Zimov, J.P. Chanton, D. Verbyla, and F.S. Chapin III. 2006. Methane bubbling from Siberian thaw lakes as a positive feedback to climate warming. Nature 443(7): 71-75.

Chapter 7. Trends in Selected Biomes, Habitats and Ecosystems: Marine and Coastal Habitats

AUTHORS: Soumitri Das[1], Corinna Ravilious[1], Lera Miles[1]
REVIEWERS: Serge Andréfouët[2], Marjo Vierros[3], Jihyun Lee[4], Chandra Giri[5]

1 UNEP World Conservation Monitoring Centre, 2 Institut de Recherche pour le Développement, 3 United Nations University, 4 Secretariat of the Convention on Biological Diversity, 5 SAIC EROS Data Center

Remote sensing based indicators for marine and coastal habitats

- Extent of coral reef ecosystems
- Percent cover of living coral
- Coral bleaching – direct observation
- Coral bleaching – temperature proxy
- Extent of seagrass ecosystems
- Extent of mangrove ecosystems
- Mangrove habitat conversion (resulting from aquaculture, agriculture, etc.)
- Changes in mangrove extent resulting from natural hazards (e.g., tsunami)
- Change in extent of mangroves, coral or seagrass as a result of regeneration or restoration
- Biomass of mangroves
- Connectivity between mangroves and their associated ecosystems

7.1 Introduction to the Remote Sensing of Coral Reefs, Seagrasses, and Mangroves

Certain marine and coastal habitats can be mapped and/or assessed using remote sensing. These include coral reefs, seagrasses, kelp beds, and mangroves, as well as polar habitats such as sea ice. Remote sensing has more frequently been used in mapping tropical rather than temperate areas as the visibility through the water column is generally better. Long-term threatening processes (such as the development of aquaculture and urbanization in coastal areas, changes in ocean temperature, or river discharge) and short-term threats (such as spreading oil spills or algal blooms) can also be monitored remotely. Some remote sensing programmes also monitor individual marine species, using telemetry (e.g., Blumenthal et al. 2006), or factors controlling their distribution, such as algal blooms (e.g., Burtenshaw et al. 2004).

7.1.1 Coral reefs

Coral reefs are among the world's most diverse and spectacular ecosystems. A coral reef is a "physical structure which has been built up, and continues to grow over decadal time scales, as a result of the accumulation of calcium carbonate laid down by hermatypic corals and other organisms" (Spalding et al. 2001). Reefs can form an integral part of coastal ecosystems, with functional relationships to seagrass beds, sandflats, mangroves, and algal plains. They provide ecosystem goods and services, including protection from tropical storms, reef fisheries, tourism opportunities, building material, and development of new pharmaceuticals (Spalding et al. 2001). The extent of coral reefs can be reduced through physical damage, bleaching, sedimentation, or pollution-induced die-off.

Coral reefs and seagrasses (below) generally occur in shallow clear waters, making them amenable to optical remote sensing. Coral reef mapping has been carried out using various satellite and airborne remote sensing methods.

7.1.2 Seagrasses

Seagrasses are rooted, underwater marine flowering plants and are not closely related to terrestrial grasses. About 60 species are known, ranging in form from the more-than-4-metre long straplike blades of eelgrass (*Zostera caulescens*) to tiny, 2–3-centimetre rounded leaves of sea vine (*Halophila decipiens*). They are an important source of food for dugong, manatee, sea turtle, and waterfowl and provide habitat for many fish and shellfish. In addition, seagrasses filter coastal waters and help to provide stability in near-shore environments by dissipating wave energy and anchoring sediments. Seagrasses often occur in proximity to, and are ecologically linked with, coral reefs, mangroves, salt marshes, bivalve reefs, and other marine habitats (Green and Short 2003). Seagrass beds may be lost as the result of dredging or other physical damage, or pollution.

7.1.3 Mangroves

Mangroves are highly productive ecosystems located in intertidal tropical and subtropical regions. They comprise a diverse group of plants (mainly trees and shrubs) that live in salt and brackish waters. They provide habitat for a wide variety of species with a rich genetic diversity. In particular, they act as a nursery ground for many juvenile fish and other marine animals. Mangroves act as buffer zones between terrestrial and marine ecosystems, stabilizing coastlines and river banks, and therefore play an important role in the functioning of adjacent ecosystems, such as salt marshes, seagrass beds, and coral reefs. They are also of great economic importance and often provide valuable ecosystem goods and essential services for local communities (Spalding et al. 1997). More recently, studies have highlighted the important function

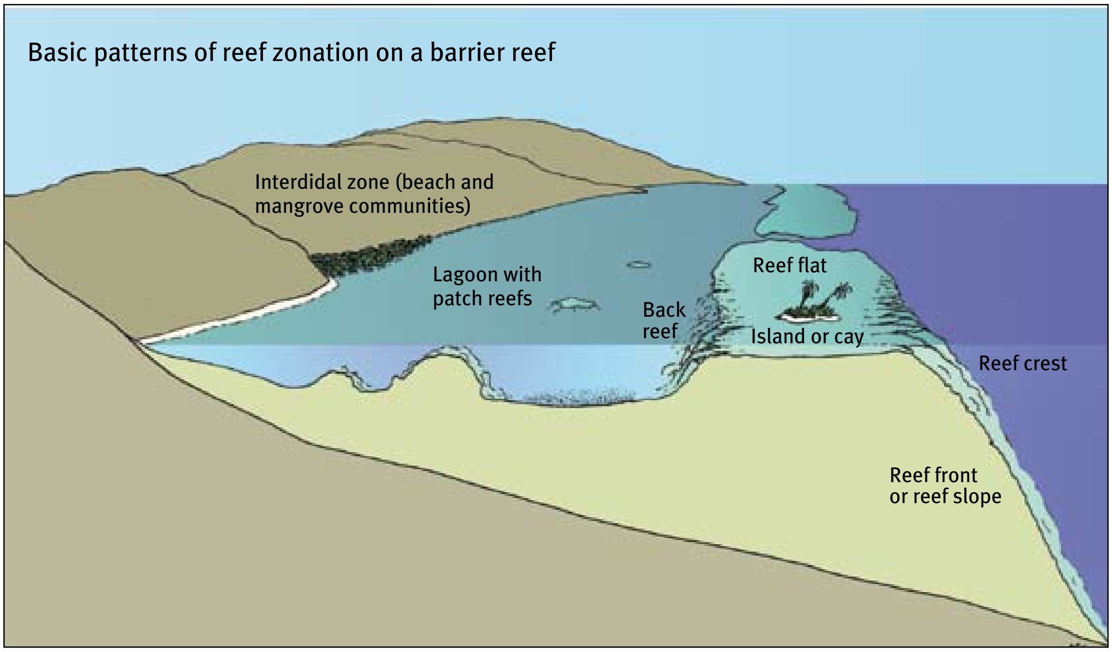


FIGURE 7.1 Patterns of zonation on a barrier reef (Spalding et al. 2001).

of mangrove forests in reducing the impact of natural disasters such as tsunamis and hurricanes. They provide a physical barrier, absorb energy, and reduce erosion (Danielsen et al. 2005; UNEP-WCMC 2006). Reductions in the extent of mangroves usually result from coastal development such as shrimp farming.

7.2 Remote Sensing Measures of Coral Reefs and Seagrasses

7.2.1 Delineating cover and estimating change in extent

Optical remote sensing typically penetrates clear waters to 15- to 30-metre depth (Mumby et al. 2004). Much research has been undertaken into remote sensing techniques for mapping shallow-water ecosystems such as coral reefs and seagrasses. Remote sensing using high-resolution multispectral images is helping to develop baseline maps of the extent, diversity, and condition of coral reefs and seagrasses. A typical coral reef has recognizable zones with different depths and communities: the forereef, reef crest, reef flat, backreef, and lagoon (in barrier reefs and atolls). See figure 7.1. These zones are amenable to optical remote sensing with moderate to high-resolution sensors, because they occur at scales of 10s to 100s of metres (Mumby et al. 2004).

When aiming to distinguish a smaller number of habitat classes (such as corals, algae, sand, and seagrasses), moderate-scale multispectral imagery is often used. The most cost-effective satellite sensors for these purposes are Landsat TM and ETM+), ASTER, and SPOT XS, with a 20–30-metre resolution. (See figure 7.2.) These sensors provide overall accuracies of about 70 percent when atmospheric and water column correction is undertaken in addition to geometric correction, with the accuracy decreasing with the number of classes distinguished (Andréfouët et al. 2003). Mapping is also increasingly being carried out using higher-resolution optical sensors such as IKONOS or QuickBird. There are some trade-offs between the higher spatial resolution and lower spectral resolution; if aiming to distinguish between coral reef communities rather than broader habitat classes, higher spectral resolution appears more important (Mumby et al. 2004).

Acoustic sensors, dragged behind boats, have also been used for habitat mapping and bathymetry to greater depths, but can cover only small areas. Boat-borne laser sensors have also been found useful in distinguishing different communities through their fluorescence spectra, but this technology is still in the research phase (Mumby et al. 2004).

The following guidelines are based on a review of research that targets small selected sites. Adaptations may be required for operational work over larger areas; it is worth consulting an experienced analyst.

Although geometric, atmospheric, and radiometric[1] corrections are routinely carried out for most remote sensing applications, underwater habitat mapping using optical sensors requires an additional water column correction because the depth and colour of water significantly affects the measurements. Green et al. (2000) describe a fairly straightforward correction technique for clear waters observed using imagery with more than two water-penetrating spectral bands (e.g., Landsat TM).

As a first step in producing habitat maps, the analyst is advised to manually segment the image in broad zones of interest to avoid areas of different thematic meaning, but with similar spectral signatures (Andréfouët and Guzman 2005). This is *a priori* contextual editing: the application of knowledge about where habitats can occur and other knowledge possessed by experts familiar with the area under analysis.

Habitat maps can then be produced using supervised multispectral image classification. This method integrates data from field surveys (carried out to define habitat categories, make training sets, and make

1 Atmospheric corrections are important because the atmosphere can contribute to up to 90 percent of the signal received by the sensor over clear oceanic waters. Radiometric corrections reduce the effects of striping and banding, which are more visible over aquatic environments (Palandro et al. 2003a).

an independent assessment of map accuracy) and prior knowledge of the interpreter. If necessary, unsupervised classification could also be carried out.

Image classification should be followed by *a posteriori* contextual editing. In this step, misclassified habitats are recoded to the correct habitats: for example, seagrass is occasionally misclassified as coral reef (especially when coral reefs include significant levels of macroalgae), but because seagrass is not found in the forereef, apparent seagrass patches on the forereef can be recoded as coral.

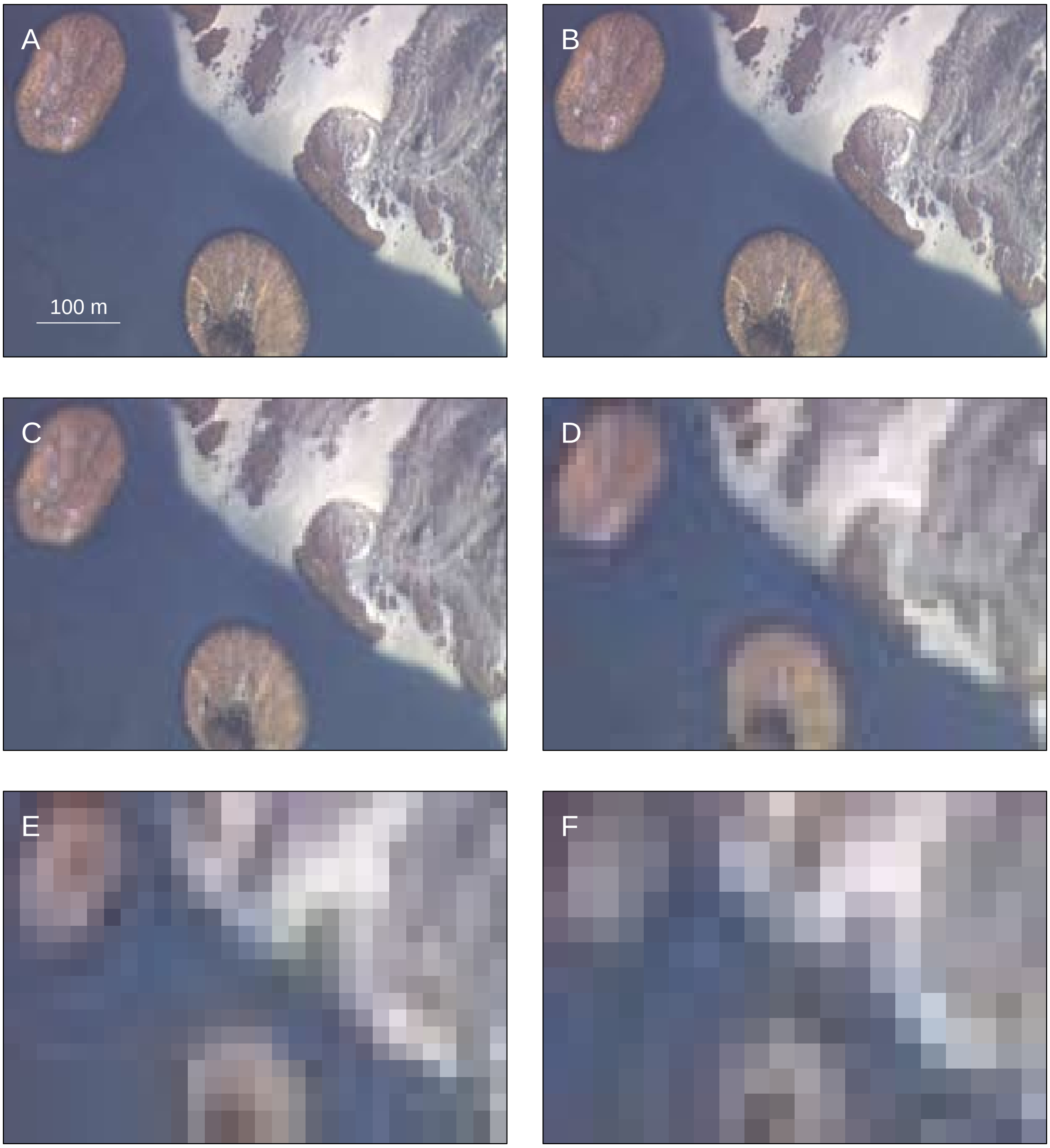


FIGURE 7.2 Backreef and lagoonal environment of Kaneohe Bay, Oahu, Hawaii, at simulated pixel resolutions common to multi- and hyperspectral remote sensing systems. A: 1 metre (aerial imaging). B: 2 metres (aerial imaging, QuickBird). C: 4 metres (aerial imaging, IKONOS). D: 10 metres (several proposed spaceborne systems). E: 20 metres (AVIRIS, SPOT). F: 30 metres (Landsat). Source: Mumby et al. 2004. ©Elsevier

The accuracy of moderate resolution imagery in mapping these marine habitats decreases with increasing habitat complexity. For intermediate and fine-scale habitat mapping, higher-resolution imagery is required. For example, data from digital airborne multispectral instruments such as the Compact Airborne Spectrographic Imager (CASI) can be used to map fine-scale habitat (that includes 13 habitat classes) with an accuracy of about 81 percent (Mumby et al. 1998; Green et al. 2000). The processing required is similar to that required for coarse-level habitat mapping. Although colour aerial photography offers similar levels of accuracy, CASI is more cost-effective. IKONOS 4-metre multispectral imagery has also been tested for habitat mapping (Andréfouët et al. 2003). IKONOS 4-metre imagery can be used to map the boundary of habitat patches with greater accuracy than with other satellite sensors, but was less accurate overall than CASI imagery (see table 7.1).

7.2.2 Additional indicators for coral reefs and seagrasses

Monitoring of coral reefs and seagrasses is usually undertaken at a local level. To obtain a regional perspective on threats to these ecosystems, these monitoring efforts must be related to adjacent land use. Changes in land use result in changes in sedimentation and pollution patterns, which have direct impacts on coral reefs (Bellwood et al. 2004).

Underwater field survey methods have been used extensively for monitoring coral reefs and seagrasses. Plotless belt transects (using a manta tow technique) enable a wide area to be surveyed at a relatively coarse scale. Change assessments may cover the extent of hard and soft coral, sand, macroalgae, and bleaching. At finer resolutions, more detailed methods, including quadrat surveys, line intercept transects, and video transects are used. Quadrat sampling and linear transects provide a relatively rapid and cost-effective method; however, linear transects tend to underestimate the area of coral cover where it occurs at low density. Data collected via photo-quadrats are useful for site monitoring, but less effective for survey over wide areas because interpretation is time-consuming. Video transects also provide a highly effective sampling method, but incur a high cost in survey and data-processing equipment.

Landsat data time series (Landsat 5 TM and Landsat 7 ETM+) offer a cost-effective resource for large-scale reef surveys and for detecting large changes in coral or seagrass extent over time. TM-ETM+ data normalization may be required to compensate for the difference in relative spectral response between TM and ETM+ (Palandro et al. 2003a). An alternative methodology uses changes in albedo in unclassified TM images to detect loss of coral-dominated area (Dustan et al. 2001).

If the habitat patches have already been mapped, IKONOS data can be used to measure small changes in patch location and boundary (Mumby and Edwards 2002). Palandro et al. (2003b) have demonstrated the potential utility of combining aerial photographs and IKONOS imagery to detect change in coral reef communities.

Coral bleaching, the loss of symbiotic algae in response to stress (such as increased temperature), can be detected remotely because it involves a change in colour. However, very high spatial resolution (less than 1 metre) imagery seems to be required to accurately quantify the extent of bleaching (Andréfouët et al. 2002), with partially bleached corals being particularly hard to identify. Because there are empirical relationships between sea surface temperatures and the likelihood of bleaching, temperature measurements can be used to estimate the strength of bleaching episodes. The NOAA Coral Reef Watch "HotSpot" data set provides a 50-kilometre resolution monitoring of heat stress to coral reefs worldwide, based on Advanced Very High Resolution Radiometer (AVHRR) measurements (Strong et al. 2004). HotSpots are cells that have experienced sea surface temperature more than 1°C above background levels. Degree heating weeks (DHWs) indicate the accumulation of thermal stress that coral reefs have experienced over the previous 12 weeks.

TABLE 7.1 Scale and accuracy: indicative figures from different remote sensing studies of coral reefs and seagrasses.

Sensor	Technique	Scale	No. of classes	Accuracy	Source
CASI	Supervised	2m	13	81%–89%	Mumby et al. 1998; Green et al. 2000
Landsat TM	Supervised	30m	4	73%	Green et al. 2000
SPOT (1–3) XS		20m	4	67%	
SPOT (1–3) P merged with Landsat MSS		10m with 30m	4	<60%	
SPOT (5) XS	Supervised	10m	2	87%–96%	Pasqualini et al. 2005
SPOT (5) P		2.5m	2	73%–89%	
Coastal Zone Colour Scanner	Neural-based	1km	2	92%–95%	Calvo et al. 2003
Coastal Zone Colour Scanner	Unsupervised	1km	2	81%–85%	Calvo et al. 2003
IKONOS	Supervised – method varied with site	4m	4–14 (10 sites)	45%–81% (greatest with fewest classes)	Andréfouët et al. 2003
Landsat ETM+		30m	4–10 (8 sites)	42%–71% (greatest with fewest classes)	
IKONOS	Supervised	4m	3–9 (same site)	84%–86% (3) 70%–74% (9)	Capolsini et al. 2003
MASTER (MODIS ASTER simulator)		20m		85%–98% (3) 42%–61% (9)	
Landsat ETM+		30m		83%–95% (3) 46%–61% (9)	
ASTER		15m		80%–85% (3) 50%–58% (9)	
QuickBird	Unsupervised from albedo	2.4m	3 (coral, sand, seagrass)	81%	Mishra et al. 2006

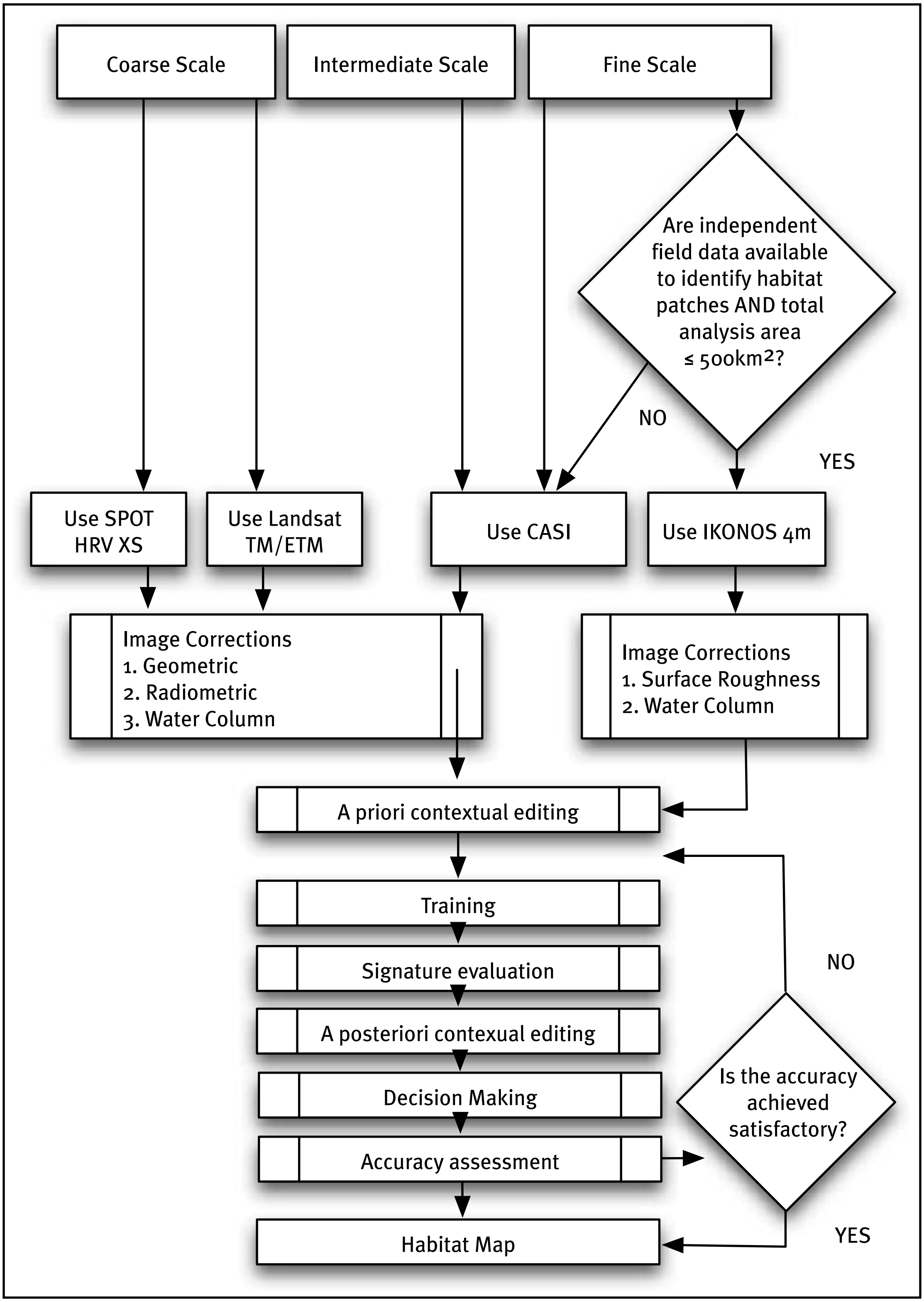


FIGURE 7.3 Flow diagram of example procedure for mapping coral reefs and seagrasses, using supervised classification (adapted from Green et al. 2000).

7.3 Remote Sensing Measures in Mangroves

There are many auxiliary data sets at global, regional, national, and local scales that can be useful to support remote sensing of this ecosystem. Field surveys provide the most important supplementary information in the remote sensing of mangrove ecosystems. The United Nations Environment Programme World Conservation Monitoring Centre (UNEP-WCMC) manages a global mangrove data set compiled from a wide range of sources at scales from 1:10,000 to 1:1,000,000, including processed satellite imagery for some areas. These data may be useful in initial identification of tiles required to map a particular habitat and, in some areas, may assist in ground-truthing imagery analysis. In turn, products derived from remote sensing may be used to update these global data sets to a higher level of detail. High-resolution elevation data sets (e.g., the Shuttle Radar Topography Mission [SRTM]) may also be useful for masking out areas that cannot contain mangroves, but the user needs to be aware of their limitations. There is, for example, a known coastline definition problem in SRTM products and their resolution (80 metres [262.5 feet]) is lower than most moderate-resolution satellites. Aerial photographs can also provide supporting information and have extensively been used in the past.

7.3.1 Delineating cover and estimating change in extent

Quantifying the true extent of mangroves can be difficult because there is no universal definition. Published statistics may refer to different components of a mangrove ecosystem, ranging from the individual mangrove forest stand through to the entire ecosystem (e.g., including rivers, creeks, and sediments) (Blasco et al. 1998). Hence, categorizing the components of the mangrove ecosystem is essential for undertaking comparative analyses. Techniques for mapping mangroves differ somewhat from those used to map coral reef and seagrass ecosystems. The same standard preprocessing techniques (geometric, atmospheric, and radiometric correction) should be applied, but there is no need to apply a water-column correction because the mangrove canopy is above the water surface. Atmospheric correction is important, particularly in tropical and subtropical coastal areas where air humidity is high (Blasco et al.1998).

Remote sensing has been used extensively with a high level of accuracy to discriminate between mangrove and non-mangrove areas. Mangroves can be distinguished by both colour and texture, but in some cases can be confused with other vegetation classes. Some studies have produced more detailed classifications, identifying between two and seven classes of mangrove vegetation (e.g., Green et al. 2000; Giri and Delsol 1995). Common sets of classes include:

- Species associations. Stands composed of characteristic species.
- Dominant species. At present, it is not possible to distinguish all of the ~60 possible mangrove tree species individually. There is some spectral distinction at the generic level (e.g., *Rhizophora, Avicennia*).
- Tree density (e.g., low, medium, high)
- Percent canopy closure
- Fringing / mixed / shrubby / logged / or cleared mangrove

Contextual editing before image processing is important for masking the image to focus on the area of interest (i.e., excluding water and land areas that are unlikely to contain mangrove). This reduces the effect of surrounding vegetation types in the image processing and thus improves the accuracy of the classification. Field data can be used to guide image classification (e.g., by providing information on location, species composition, and canopy height and density).

The sensors most often used in mangrove mapping are Landsat, SPOT, Synthetic Aperture Radar (SAR), CASI, IKONOS, and IRS. Selecting the right band combination helps to enable distinction of mangroves from other classes: for example, typical band combinations for mapping mangroves from Landsat are 543, 431, or 432.

A variety of techniques have been used successfully to map mangrove ecosystems. The most appropriate method depends upon scale and the required outputs. For medium-scale mapping, Landsat and SAR data have been used quite extensively. Five main image-processing techniques have been used (Green et al. 2000), all relying upon remote sensing software packages such as ENVI and ERDAS IMAGINE:

1. **Visual interpretation**. A linear contrast stretch is performed, and then the imagery is visually interpreted using other maps and field data.
2. **Band ratios**. The pixels in one image are divided by the corresponding pixels in another (for the same location) to obtain the ratio. These values can then be classified using techniques 4 and 5.
3. **Vegetation indices.** Such as the normalized difference vegetation index (NDVI), which transform two or more bands into a single index. These values can then be classified using techniques 4 and 5.
4. **Unsupervised classification**. The spectral properties of an image are used to group pixels into classes, with no interference by the user.
5. **Supervised classification**. The spectral properties of an image are used to group pixels into classes, using expert knowledge/field data to control the classification.

Change detection requires comparable data sets to produce useful and accurate results. A high level of accuracy (in both preprocessing and image classification) is particularly important when undertaking change analysis. For example, root mean square (RMS) error in geometric correction should be less than one-half pixel. In change detection analyses, it is preferable that information be derived from the same or similar image sources (e.g., Landsat images from 1990 and 2000) and both processed using a consistent technique.

Some change detection analysis has been undertaken for mangroves. There is no standard methodology for delineating change, but a variety of methods have been used. NDVI can be used to assess change by calculating NDVI for each image date, followed by unsupervised classification of the resultant images. Statistical tests are used to assess those areas that have undergone change (Upanoi and Tripath 2003). Band ratioing (using bands 4/3 and 7/4) has also been used successfully. This has predominantly used multidate Landsat images followed by unsupervised classification to create classes, such as a range from unhealthy to healthy mangrove (Archer et al. 2003). Visual interpretation can be used, but requires greater expert knowledge and user input (Wang et al. 2003). As with mapping distribution, it is useful to obtain field survey data for validation and to improve the accuracy of the classification. For example, in French Guiana, a combination of remote sensing and field surveys was used to assess its dynamic coastline over the past 50 years (where discharges from the Amazon have created a mobile environment of mud banks and mangrove forests). The results of the study showed alternating phases of net accretion (1951–1966 and 1991–present) and net erosion (1966–1991), in which the mangrove forest dynamics were reflected by the growth stages and structure of mangrove forest stands (Fromard et al. 2004). Such integrated analysis of the coastal dynamics and mangrove development has shown how they are closely related. Information such as this could be expanded up to a regional or global context.

7.3.2 Limitations

Imagery at very coarse resolutions (e.g., 1-kilometre AVHRR) does not effectively or accurately map mangroves to provide useful information for scientists and resource managers, even at the global scale. Therefore, this can be excluded as a viable information source. Remote sensing becomes a more useful tool at moderate resolutions (e.g., using imagery less than or equal to 30 metres).

Although remote sensing can be used to produce mangrove maps with high levels of accuracy, it is important to be aware of several potential sources of inaccuracy and confusion. Mangroves with a dense canopy may obscure treeless patches and channels, therefore augmenting the actual area of mangroves. Overestimation will be increased in areas of low density or in areas where mangroves grow in small patches. The degree to which this is a problem depends upon whether "mangrove area" is defined as including the entire mangrove ecosystem (including creeks and channels) or purely the individual mangrove stands (Kannan et al. n.d.). Extent may be underestimated where mangroves occur in small patches beyond the spatial resolution of some sensors. This highlights the importance of identifying which components of the ecosystem are to be mapped, selecting the appropriate sensor for the area of interest, and having an awareness of the types of mangrove that are likely to occur there.

Lack of spectral detail in multispectral sensors has caused difficulty in accurately distinguishing mangrove areas from other nonmangrove vegetation. In tropical areas, for example, distinction between mangroves and swamp forest is known to be problematic. SPOT XS, while successful in mapping mangroves in some areas, has been known to require additional inputs from other mapped or image sources in other areas. For example, Green et al. (2000) found that in the Turks and Caicos Islands, mangroves could not be distinguished from adjacent thorn scrub. Multispectral satellite imagery does not accurately distinguish mangroves of differing species compositions (distinguishing only 1–2 classes of dominant species, compared with 8–10 individual species classes obtained by finer resolution hyperspectral sensors such as HYPERION (220-band) and Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) (224-band). For multispectral sensors, a lack of spectral detail can be a limitation, especially when mapping down to the species level. Physiochemical properties of plants (such as chlorophyll content) are linked to spectral responses; therefore, with the broad wavelength bands of multispectral sensors, which cover several tens of nanometres, this information is lost (Vaiphasa et al. 2005). Hyperspectral sensors offer greater potential for mapping density and coverage of mangroves by species (Jupiter et al. 2003), although their effectiveness for tropical mangrove species discrimination has yet to be proven. Vaiphasa et al. (2005) discriminated 16 species with 95 percent confidence, but did highlight difficulty in distinguishing mangrove species in the *Rhizophoraceae* family.

Cloud cover is often a problem when mapping mangroves using optical sensors. Radar, however, can penetrate clouds and is capable of mapping at moderate and high resolutions (range 8–100 metres) as well as assessing biomass. Early research into mapping mangroves using radar suggests difficulty in achieving high accuracy levels (accuracies ~50 percent); however, limited published research is available (Green et al. 2000; Hashim and Wam Kadir 1999).

Combined approaches to enhance resolution of imagery and provide better mangrove delineation can be used. For example, combining radar imagery (e.g., ERS-1 SAR) with optical sensors (e.g., SPOT) has shown high levels of accuracy (84 percent), as well as providing additional information on age of mangrove stands (Aschbacher et al. 1995). However, spectral quality can be reduced (e.g., when applying a resolution merge to a Landsat 15-metre resolution panchromatic band with a 30-metre spectral band). To optimize speed and performance, it is recommended that large amounts of disk space and equipment with high levels of processing power be available for undertaking this type of analysis.

Digital airborne multispectral imagery such as CASI also produces high levels of accuracy. Using supervised classifications, CASI provides greater levels of detail and accuracy than with other optical sensors—and even higher levels using band ratio techniques (Green et al. 2000). However, high-resolution satellite imagery such as QuickBird and IKONOS now challenge this type of sensor. Imagery at 1–4-metre resolution provides highly accurate assessment of mangroves at the species level (Green et al. 2000; Wang et al. 2004). Permanent monitoring at a global scale at such a fine resolution is not practical because of the number of images required for processing, but a repeated sampling scheme could be feasible.

7.3.3 Additional indicators for mangroves

Research suggests that mangrove leaf area index (LAI) can be mapped (based on NDVI) using IKONOS sensors. LAI change is related to growth and change in canopy structure. Comparisons of LAI readings obtained in the field with those obtained from remote sensing suggest that this technique could be particularly useful for mapping change in inaccessible areas of mangrove or where field survey is not possible. Although initial investigations have produced significant results, further testing is required (Green et al. 2000; Wang et al. 2004; Kovacs et al. 2004). It may also be possible to use LAI data in modelling expected future growth and in comparing monitored changes in canopy structure resulting from pollution and climate change.

Remote sensing can be used to look at the connectivity between mangroves and their associated ecosystems, in particular in terms of its role in buffering of sediment between marine and terrestrial environments. Remote sensing provides opportunity to evaluate how changes in land use can impact directly upon mangroves and in turn impact upon coral reef and seagrass ecosystems. Few studies to date have used remote sensing to assess this role, but there is great potential for monitoring the impacts of change in terms of mangrove condition (e.g., extent [both loss and new growth] and canopy cover, sedimentation, and hydrology). In this way, remote sensing becomes an increasingly valuable tool for making future predictions, highlighting key areas of threat, and identifying critical sites for restoration and protection (Jupiter et al. 2003).

7.3.4 Scale and accuracy

The major advantage of using remote sensing to map mangroves is that many areas, especially the interiors of mangrove regions, are difficult or impossible to access and survey. Monitoring of mangroves using remote sensing is already being undertaken at local and national levels; however, regional- and global-level studies have not yet been carried out. Studies have shown that there is some potential to scale up local and national studies by looking at mangrove zonation patterns alongside associated coastal and ecological processes. These can potentially be used to predict zonation and change at regional levels (Fromard et al. 2004).

Mangrove assessment using remote sensing at local and national levels will eventually need to be placed in a global context to be able to accurately assess the impacts of climate change and sea level rise. Remote sensing could be used in the long-term to monitor ecological processes and predict ecosystem response.

Few published studies for mangrove include an accuracy assessment, which makes it difficult to compare methods used (see Table 7.2 for some exceptions.) Accuracy is dependent upon the resolution of the satellite image, the processing methods used (including the number of classes distinguished), and the availability of field data. Further studies are required that make use of the more recent higher-resolution sensors, with resolutions of 5–10 metres. These may be useful in the further delineation and monitoring of change in mangrove classes at the local level.

To accurately assess change at the national scale, a baseline mapped at a consistent scale using a consistent technique is required. Remote sensing provides a fast, efficient, and valuable tool for fulfilling this need for up-to-date information and the ability to monitor change accurately over time. For example, in Tanzania, remote sensing is used in coastal resource management and ecosystem monitoring (Wang et al. 2003). Mangroves along the Tanzania coast are protected under the Mangrove Management Project

(MMP). Landsat imagery has been used, together with field data, to monitor change and the effectiveness of mangrove conservation and sustainable use measures.

To date, analysis of remote sensing data has been undertaken mainly for mangrove inventory and the preparation of distribution maps. A few studies mapped additional information such as tree height or density, but at present these do not provide clear quantitative comparisons between sites. There are no regional- or global-level mangrove assessments mapped from remote sensing, with the exception of the inclusion of a mangrove class in land cover maps such as the 1-kilometre Global Land Cover 2000 data set (Bartholome and Belward 2005).

TABLE 7.2 Scale and accuracy: indicative figures from different remote sensing studies of mangroves

Sensor	Technique	Scale	No. of classes	Accuracy	Source
Landsat TM	Unsupervised NDVI; linear regression model to calibrate NDVI into leaf area index (LAI) and canopy closure (CC).	30m	-	71% (LAI) 65% (CC)	Green et al. (2000)
SPOT (1–3) XS		20m	-	88% (LAI) 76% (CC)	
CASI		2m	-	94% (LAI) 80% (CC)	
CASI	Band ratios	2m	9	85%	Green et al. (2000)
	Supervised			78%	
	Unsupervised			70%	
SPOT (1–3) XS	Unsupervised	20m	4	95%	Vits and Tack (1995), cited in Green et al. (2000)
Landsat TM	Unsupervised	30m		97%	
SPOT (1–3) XS	Supervised	20m	4	91%	
SPOT (1–3) XS	Supervised	20m	2	81%	Palaganas (1992), cited in Green et al. (2000)
IRS-1C	Supervised	23.5m	3	98%	Satyanarayana, B. (1999?), cited in Green et al. (2000)
Landsat ETM+	Visual interpretation	30m	4	98%	Wang et al. (2003)
SPOT (1–3) XS	Supervised (various sensor combinations and analysis techniques)	20m	4	84%	Aschbacher et al. (1995); Giri and Delsol (1995)
ERS-1 SAR		30m		48%	
JERS-1 SAR		18m		48%	
Landsat TM		30m		73%	

Sensor	Technique	Scale	No. of classes	Accuracy	Source
JERS-1 SAR	Supervised/ unsupervised	18m	7	52%	Hashim and Wan Kadir (1999)
Radarsat SAR	Supervised/ unsupervised	25m	5	46%	
JERS-1 SAR	Regression analysis (relationship of mangrove biomass to radar backscatter)	18m	-	40%	
Radarsat SAR		25m	-	37%	
IKONOS	Supervised	1m / 4m	3 (species)	75%	Wang et al. (2004)
QuickBird	Supervised	0.7m / 2.8m	3 (species)	72%–73%	

7.4 Data and Other Resources

Various publications offer guidance on remote sensing analysis within marine and coastal habitats (St Martin 1993, Andréfouët *et al*. 2002, IGOS 2003). There are also many spatial data sets of coral reefs and seagrasses at global, regional, national, and local scale that can be useful in evaluation or ground-truthing of remote sensing data for these ecosystems. Some global-scale resources are listed below.

ReefBase

ReefBase forms an online information system on coral reefs, including downloadable GIS data sets on coral extent, spawning, bleaching, and diseases.

http://www.reefbase.org

The Millennium Coral Reef Mapping Project and Millenium Coral Reefs Landsat Archive

Supported by NASA, the Institute for Marine Remote Sensing at the University of South Florida is developing the first global uniform map of shallow coral reef ecosystems. The Millennium Coral Reef Mapping Project has collated a global compilation of ~1,700 Landsat 7 ETM+ satellite images, with 30-metre spatial resolution (Andréfouët et al. 2006). A thematically rich (966 classes) geomorphological classification scheme was designed and used to interpret and map shallow coral reef systems worldwide. The resulting globally consistent GIS products are expected to be released through ReefBase sometime in 2007.

Meanwhile, an archive of Landsat imagery is already available. The Landsat Coral Reef Data Archive displays data that is tiled, zoomable, and downloadable via FTP.

http://oceancolor.gsfc.nasa.gov/cgi/landsat.pl

The University of South Florida maintains a site where an index with browse images of all the Landsat 7 data is assembled.

http://imars.marine.usf.edu/corals/maps/reef_count.html

Global Mangrove Database and Information System (GLOMIS)

GLOMIS resources, managed by the International Society for Mangrove Ecosystems, include a searchable online reference database of mangrove literature.

http://www.glomis.com

NOAA Coral Reef Watch HotSpots

Sea surface temperature anomalies, bleaching HotSpot anomalies, Degree Heating Weeks (DHWs), and Tropical Ocean Coral Bleaching Indices are available on an operational basis at the global scale.

Introduction: http://coralreefwatch.noaa.gov/index.html

Latest data: http://www.osdpd.noaa.gov/PSB/EPS/SST/climohot.html

UNEP World Conservation Monitoring Centre

UNEP-WCMC hosts a global-scale Geographic Information System (GIS) database of vector and raster data of coral reefs and seagrasses, compiled from a wide range of sources at scales ranging from 1:10,000 to 1:1,000,000, and including processed satellite imagery. The *World Atlas of Coral Reefs* provides global estimates for coral reefs worldwide and presents reef area estimates for individual countries, supported by maps and statistics for all coral reef nations (Spalding et al. 2001). The *World Atlas of Seagrasses* contains the first global and regional maps of seagrass distribution (Green and Short 2003). Although these atlases were the first to provide comprehensive data on coral reefs and seagrasses, more detailed data sets are subsequently being developed.

http://www.unep-wcmc.org/

7.5 References

Andréfouët, S., R. Berkelmans, L. Odriozola, T. Done, J. Oliver, and F. Muller-Karger. 2002. Choosing the appropriate spatial resolution for monitoring coral bleaching events using remote sensing. Coral Reefs 21 (2): 147-154.

Andréfouët, S., and H.M. Guzman. 2005. Coral reef distribution, status, and geomorphology-biodiversity relationship in Kuna Yala (San Blas) archipelago, Caribbean Panama. Coral Reefs 24 (1): 31-42.

Andréfouët, S., P. Kramer, D. Torres-Pulliza, K.E. Joyce, E.J. Hochberg, R. Garza-Pérez, P.J. Mumby, B. Riegl, H. Yamano, W.H. White, M. Zubia, J.C. Brock, S.R. Phinn, A. Naseer, B.G. Hatcher, and F.E. Muller-Karger. 2003. Multi-site evaluation of IKONOS data for classification of tropical coral reef environments. Remote Sensing of Environment 88.1-2: 128-143.

Andréfouët, S., F.E. Muller-Karger, J.A. Robinson, C.J. Kranenberg. D. Torres-Pulliza, S.A. Spraggins, and B. Murch. 2004. Global assessment of modern coral reef extent and diversity for regional science and management applications: a view from space. Proceedings of the 10th International Coral Reef Symposium, June 28-July 2, 2004. Japanese Coral Reef Society, Tokyo, Japan.

Archer T.A., J.M. Kovacs, and L.P. Aspden. 2003. Monitoring the decline of a tropical forested wetland of the Teacapán estuarine system, Mexico. Proceedings of the 25th Canadian Symposium on Remote Sensing 2003. Canadian Aeronautics and Space Institute.

Aschbacher, J., P. Tiangco, C.P. Giri, R.S. Ofren, D.R. Paudyal, and Y.K. Ang. 1995. Comparison of different sensors and analysis techniques for tropical mangrove forest mapping. Proceedings of the 16th Asian Conference on Remote Sensing (ACRS), November 20-24, 1995. Suranaree University of Technology, Nakhon Ratchasima, Thailand.

Bartholome, E., and A.S. Belward. 2005. GLC2000: A new approach to global land cover mapping from Earth. International Journal of Remote Sensing 26:1959-1977.

Bellwood, D.R., T.P. Hughes, C. Folke, and M. Nystrom. 2004. Confronting the coral reef crisis. Nature 429 (6994): 827-833.

Blasco, F., T. Gauquelin, M. Rasolofoharinoro, , J. Denis, , M. Aizpuru, and V. Caldairou 1998. Recent advances in mangrove studies using remote sensing data. Marine and Freshwater Research 49: 287–296.

Blumenthal, J.M., J.L. Solomon, C.D. Bell, T.J. Austin, G. Ebanks-Petrie, M.S. Coyne, A.C. Broderick, and B.J. Godley. 2006. Satellite tracking highlights the need for international cooperation in marine turtle management. Endangered Species Research 2: 51-61.

Burtenshaw, J.C., E.M. Oleson, J.A. Hildebrand, M.A. McDonald, R.K. Andrew, B.M. Howe, and J.A. Mercer. 2004. Acoustic and satellite remote sensing of blue whale seasonality and habitat in the Northeast Pacific. Deep Sea Research II 51 (10-11): 967-986.

Calvo, S., G. Ciraolo, and G. La Loggia. 2003. Monitoring Posidonia oceana meadows in a Mediterranean coastal lagoon (Stagnone, Italy) by means of neutral networks and ISODATA classification methods. International Journal of Remote Sensing 24 (13): 2703-2716.

Capolsini, P., S. Andréfouët, C. Rion, and C. Payri. 2003. A comparison of Landsat ETM+, SPOT HRV, Ikonos, ASTER, and airborne MASTER data for coral reef habitat mapping in South Pacific islands. Canadian Journal of Remote Sensing 29 (2):187-200.

Danielsen, F., M.K. Sørensen, M.F. Olwig, V. Selvam, F. Parish, N.D. Burgess, T. Hiraishi, V.M. Karunagaran, M.S. Rasmussen, L.B. Hansen, A. Quarto, and N. Suryadiputra. 2005. The Asian Tsunami: A protective role for coastal vegetation. Science 310 (5748): 643.

Dustan, P., E. Dobson, and G. Nelson. 2001. Landsat Thematic Mapper: Detection of shifts in community composition of coral reefs. Conservation Biology 15.4:892-902.

Fromard, F., C. Vega, C. Proisy. 2004. Half a century of dynamic coastal change affecting mangrove shorelines of French Guiana. A case study based on remote sensing data analyses and field surveys. Marine Geology 208.2-4:265-280.

Giri, C. and J.P. Delsol 1995. Mangrove Forest Cover Mapping Using Remote Sensing Data in Conjunction with GIS. Asian-Pacific Remote Sensing Journal 8.1. ESCAP (Economic and Social Commission for Asia and the Pacific), Bangkok, Thailand.

Green, E.P., and F.T. Short. 2003. World Atlas of Seagrasses. University of California Press, Berkley, 2003.

Green, E.P., P.J. Mumby, A.J. Edwards, and C.D. Clark. 2000. Remote Sensing Handbook for Tropical Coastal Management. Coastal Management Sourcebook 3. Ed. A.J. Edwards. UNESCO: Paris, 2000. http://www.unesco.org/csi/pub/source/rs.htm (accessed January, 2007).

Hashim, M., and H.H. Wan Kadir. 1999. Comparison of JERS-1 and RADARSAT synthetic aperture radar data for mapping mangrove and its biomass. 20th Asian Conference on Remote Sensing (ACRS). Hong Kong, China.

IGOS 2003. IGOS Coral Reef Subtheme Report. Integrated Global Observing Strategy. http://www.igospartners.org/docs/theme_reports/IGOS_CoralReefSubtheme.pdf. Accessed 10 May 2007.

Jupiter, S.D., Phinn, S., Duke, N.C., Potts, D.C. 2003. The Buffer Zone: Connectivity Between Mangrove and Coral Reef Ecosystems in the Context of Land Use Change. International Symposium on Remote Sensing of Environment, Honolulu, Hawaii. http://www.cms.uq.edu.au/mackayarc/publications.htm. Accessed 11 May 2007.

Kannan, L., T. T. Ajith Kumar and A. Duraisamy n.d. Remote Sensing for Mangrove Forest Management. http://www.gisdevelopment.net/application/environment/wetland/envwm0002.htm. Accessed 11 May 2007.

Kovacs, J.M., F. Flores, J. Wang, and L.P. Aspden. 2004. Estimating leaf area index of a degraded mangrove forest using high spatial resolution satellite imagery. Aquatic Botany 80: 13-22.

Mishra, D., S. Narumalani, D. Rundquist, and M. Lawson. 2006. Benthic habitat mapping in tropical marine environments using QuickBird multispectral data. Photogrammetric Engineering & Remote Sensing 72.9: 1037-1048.

Mumby, P.J., and A.J. Edwards. 2002. Mapping marine environments with IKONOS imagery: enhanced spatial resolution can deliver greater thematic accuracy. Remote Sensing of Environment 82: 248-257.

Mumby, P.J., E.P. Green, and C.D. Clark. 1998. Digital analysis of multispectral airborne imagery of coral reefs. Coral Reefs 17 (1): 59-69.

Mumby, P. J., W. Skirving, A.E. Strong, J.T. Hardy, E.F. Ledrew, E.J. Hochberg, R.P. Stumpf, and L.T. David. 2004. Remote sensing of coral reefs and their physical environment. Marine Pollution Bulletin 48 (3-4): 219-228.

Palandro, D., S. Andréfouët, F.E. Muller-Karger, P. Dustan, C. Hu, and P. Hallock. 2003a. Detection of changes in coral reef communities using Landsat-5 and Landsat-7 ETM+ data. Canadian Journal of Remote Sensing 29 (2): 201-209.

Palandro, D. S. Andréfouët,P. Dustan, F.E. Muller-Karger. 2003b. Change detection in coral reef communities using IKONOS satellite sensor imagery and historic aerial photographs. International Journal of Remote Sensing 24 (4): 873-878.

Pasquilini, V., C. Pergent-Martini, G. Pergent, M. Agreil, G. Skoufas, L Sourbes, and A. Tsirika. 2005. Use of SPOT 5 for mapping seagrasses: An application to Posidonia oceanica. Remote Sensing of Environment 94: 39-45.

Spalding, M.D., C. Ravilious, and E.P. Green. 2001. World Atlas of Coral Reefs. University of California Press, Berkley, 424 pages.

Spalding, M.D., F. Blasco, and C.D. Fields, eds. World Mangrove Atlas. The International Society of Mangrove Ecosystems. Okinawa. Japan, 1997.

St Martin, K. (ed). 1993. Explorations in Geographic Information Systems Technology. Volume 3: Applications in Coastal Zone Research and Management. Clark Labs for Cartographic Information Systems Technology and Analysis, Worcester, Mass. and United Nations Institute for Training and Research (UNITAR), Geneva, Switzerland.

Strong, A.E., G. Liu, J. Meyer, J.C. Hendee, and D. Sasko. 2004. Coral reef watch 2002. Bulletin of Marine Science 75 (2): 259-268.

UNEP-WCMC. 2006. In the front line: Shoreline protection and other ecosystem services from mangroves and coral reefs. Cambridge, UK, 2006, 33 pages.

Upanoi, T. and N.K. Tripath 2003. A Satellite Based Monitoring of Changes in Mangroves in Krabi, Thailand. Map Asia Conference 2003. http://www.gisdevelopment.net/application/nrm/coastal/mnm/pdf/ma03213.pdf. Accessed 9 May 2007.

Vaiphasa, C., S. Ongsomwang, T. Vaiphasa and A.K. Skidmore 2005. Tropical mangrove species discrimination using hyperspectral data: A laboratory study. Estuarine, Coastal and Shelf Science 65 (1-2):3 71-379.

Wang, Y., G. Bonynge, J. Nugranad, M. Traber, A. Ngusaru, J. Tobey, L. Hale, R. Bowen, and V. Makota. 2004 Remote sensing of mangrove change along the Tanzania coast. Marine Geodesy 26: 1-14.

Wang, L., W.P. Sousa, P. Gong, and G.S. Biging. 2004. Comparison of IKONOS and QuickBird images for mangrove species mapping on the Caribbean coast of Panama. Remote Sensing of the Environment 91: 432-440.

Chapter 8. Trends in Species Populations

AUTHORS: Colby Loucks[1], Peter Leimgruber[2],
CONTRIBUTORS: James Strittholt[3], Hong Jiang[3]
REVIEWERS: Sarat Babu Gidda[4]

1 World Wildife Fund (WWF-US), 2 Smithsonian National Zoological Park, 3 Conservation Biology Institute, 4 Secretariat of the Convention on Biological Diversity

Remote sensing based indicators for species populations:

- Location and extent of species aggregations
- Extent of specific habitats—direct detection
- Extent of specific habitats—indirect detection
- Extent of specific habitats—modelled

8.1 Background

Promoting the conservation of species diversity is one of the goals of the Convention on Biological Diversity's 2010 target. To effectively attain this goal and its sub-targets would require the maintenance of viable populations of selected species. In turn, this requires a sufficient number of individuals, populations (different groups of individuals occupying the same area), and habitat (the space and biophysical features required to support the species). Therefore, basic measures of species diversity include number (species richness), abundance (population size) of species, number of viable populations, and habitat area.

Remote sensing data have become vital to monitoring trends in the distribution and abundance of many plant and animal species. Two general approaches are used. The first is to directly monitor individual organisms or populations, using airborne or satellite sensors. The indirect approach is to use remotely sensed environmental data in predictive models, estimating species location within a geographic information system (GIS) or statistical package. Although direct species monitoring via remote sensing (i.e. relating spectral reflectance data to species or biodiversity distribution) is relatively uncommon, the use of distribution prediction and modelling continues to increase as new remote sensing data, modelling tools, and statistical techniques develop and mature.[1]

8.2 Remote Sensing to Directly Monitor Species Populations

Currently, population trends of only a few relatively large or very abundant plant and animal species can directly be monitored using remote sensing techniques. McGraw et al. (1998) and Key et al. (2001) demonstrated success in predicting deciduous tree species distributions, though for relatively small areas. It is possible to use satellite imagery to map the extent and change of communities of colonial organisms such as coral reefs (Mumby et al. 1997; Hochberg and Atkinson 2000, also see Chapter 7), or even individual colonies of burrowing mammals such as prairie dogs (Sidle et al. 2001). However, most direct monitoring has focused on medium to large mammals or flocks of migratory birds in open landscapes (i.e., at stopover sites or in open wetlands, grasslands, or savanna). The latter involve airplane or helicopter aerial surveys, high resolution satellite data, or a combination. Some examples of direct monitoring include white-backed vulture

1 Stauffer provides a good general overview, with caveats pertaining to distinguishing between mapping species and mapping probability of species. Henbry and Merchant (in same book) also make some relevant points (Stauffer 2002, 53–61).

(Murn et al. 2002), saiga antelope (Milner-Gulland et al. 2001), whales (Best 1990), elephants (Whitehouse et al. 2001), orangutan nests (Ancrenaz et al. 2005), and Australian mammals (Tracey et al. 2005).

The ability to directly monitor species is rare, however. The majority of species cannot be identified, counted, mapped, or monitored directly from satellite or aerial imagery for several reasons, including the size of the species in relation to sensor resolution, natural history (i.e., nocturnal species would be difficult to detect using optical sensors), and the "long return time" (i.e., the time it takes the satellite to return to the same spot on the earth for a second image). Even when detection of animals via satellite or airborne techniques is possible, there are still problems in determining whether the samples are statistically valid. Because of the number of images needed for an accurate estimate, direct monitoring will be prohibitively expensive in the near future for most candidate species.

8.3 Remote Sensing to Indirectly Monitor Species Populations: Modelling Species Distributions by Mapping Habitat

Meanwhile, examples of indirect estimates of populations and distributions derived from remotely sensed data are increasing (Turner et al. 2003). Biophysical or other environmental parameters that can be measured are used to predict the distribution of habitats and species (Kerr and Ostrovsky, 2003*)*. This approach combines knowledge of species distributions from on-the-ground field surveys with environmental parameters (e.g., habitat, elevation, rainfall) to develop an empirical model that can be applied over a much greater area (Manly et al. 2004).

The assumption that habitat area is an indicator of species richness is based on the species area relationship $S = cA^z$, where S is the number of species, A is area, and c and z are constants (Arrhenius, 1921). Assumption of this equation allows habitat classifications to infer species losses associated with changes in land cover and land use. Where local parameters (c and z) of the species-area curve have been tested, clarifying the precise relationship between species richness and habitat area, remote sensing can complete the area component of the equation (Turner et al. 2003).

Threat mapping is an indirect way of mapping a species' distribution or more precisely of mapping where species are not found. In contrast to species-habitat models that delineate areas potentially occupied by a given species, threat mapping may delineate areas that are avoided by a species. For example, Asian elephants (*Elephas maximus*) tend to be habitat generalists; they can be found in most natural environments ranging from grasslands and wetlands to dense moist forests. However, in areas of dense agriculture and human population, they have a much greater risk of being killed as the result of crop raiding and human-elephant conflict. This type of "exclusion" or threat mapping can complement habitat mapping or be used by itself. Measured trends in habitat or threat extent can be used as a proxy for trends in the species' population. Remote sensing and remotely sensed imagery are essential for this type of *indirect* monitoring of species.

A majority of the species distribution models correlate potential habitat or ecosystem properties (i.e., net primary productivity) with on-the-ground surveys to monitor population trends. However, the accuracy for mapping a specific habitat type is frequently between 75 and 85 percent. Therefore, we often cannot detect minor changes very accurately. Increasingly, scientists are attempting to map and delineate either biodiversity measures or species distribution directly from spectral reflectance information (such as Normalized Difference Vegetation Index [NDVI]) contained in satellite images (Leimgruber et al. 2005). Using NDVI, Gould (2000) estimated species richness of three vascular species in Central Canadian Arctic region. The advantage of directly relating species distribution to an environmental variable is that there is no additional error introduced through the habitat classification process.

Habitat loss is the single most important factor in species extinction (Baillie et al. 2004). Consequently, global, continental, or countrywide habitat change mapping can be an important tool in the monitoring of remaining wild populations of species. Although it should not replace systematic on-the-ground surveys and monitoring for species populations, satellite data can and should play a significant role in the following:

- establishing baseline datasets on current extent of suitable habitat for a given species;
- identifying zones for on-the-ground survey/monitoring (for example, satellite data can be used to identify areas of habitat similar to those known to be occupied by a species, or areas where species are threatened by habitat loss);
- providing early warning systems for habitat loss and potential population decline; and
- determining fragmentation and connectivity of remaining populations and metapopulations.

8.4 Practical Examples

Systematic monitoring of species populations at global to continental scales exists, but most studies have been done at the national scale or smaller. Examples of global and continental monitoring of mammals include the North American Breeding Bird Surveys (Sauer et al. 2005), monitoring of African elephants by the African Elephant Specialist Group, Monitoring the Illegal Killing of Elephants (MIKE) (http://www.cites.org/eng/prog/MIKE/index.shtml), and the Save the Tiger Fund (STF) has spearheaded an effort to identify and prioritize the remaining habitat – Tiger Conservation Landscapes (TCLs) – for tigers across their range (www.savethetigerfund.org/Content/NavigationMenu2/Initiatives/TCL/FullReports/default.htm, accessed April 2007)

Countrywide or smaller-scale species distribution models are abundant, and they are increasingly using remote sensing data. Rushton et al. (2004) analysed 21 species distribution modelling studies published in the *Journal of Applied Ecology* since 2000. Of these studies, 16 used remote sensing or mapped habitat data, often in combination with field survey data, to predict species distribution for mammals, birds, lepidoptera, and reptiles. Recent studies include the following:

Raxworthy et al. (2003) used old locality data from museums in combination with satellite data to predict the distribution of 11 chameleon species in Madagascar. They achieved an overall accuracy rate of 82 percent and also identified areas of "overprediction," where the model suggested that there were more species than had been recorded. Once these areas were surveyed, they yielded seven chameleon species new to science.

Loucks et al. (2003) used SPOT imagery to identify forest-nonforest habitat to identify potential giant panda (*Ailuropoda melanoleuca*) habitat in the Qinling Mountains of China. They combined the forest data with elevation and field data to develop a predictive model of habitat distribution and giant panda abundance. This analysis eventually led to the creation of six nature reserves to protect gaps in the giant panda's habitat.

McShea et al. (1999) used satellite maps of Eld's deer (*Cervus eldii*) habitat in Myanmar to identify remaining habitat for this highly endangered species. Koy et al. (2005) expanded on this study and used a continuous-field analysis of Landsat data to predict tree density in open-canopy dipterocarp forests, the preferred habitat by Eld's deer. They found that Eld's deer distribution was related to tree density.

Osborne et al. (2001) used Advanced Very High Resolution radiometer (AVHRR) imagery in conjunction with disturbance data to predict the distribution of great bustards in central Spain. They found that sites occupied by bustards had significantly lower densities of human-altered land (e.g., roads, buildings) and also occurred in a narrow range of elevations.

Buchanan et al. (2005) successfully combined field survey data with a supervised classification of a Landsat image to identify detailed categories of moorland vegetation. They then were able to predict golden plover (*Pluvialis apricaria*) abundance, based on habitat associations, across large moorland areas.

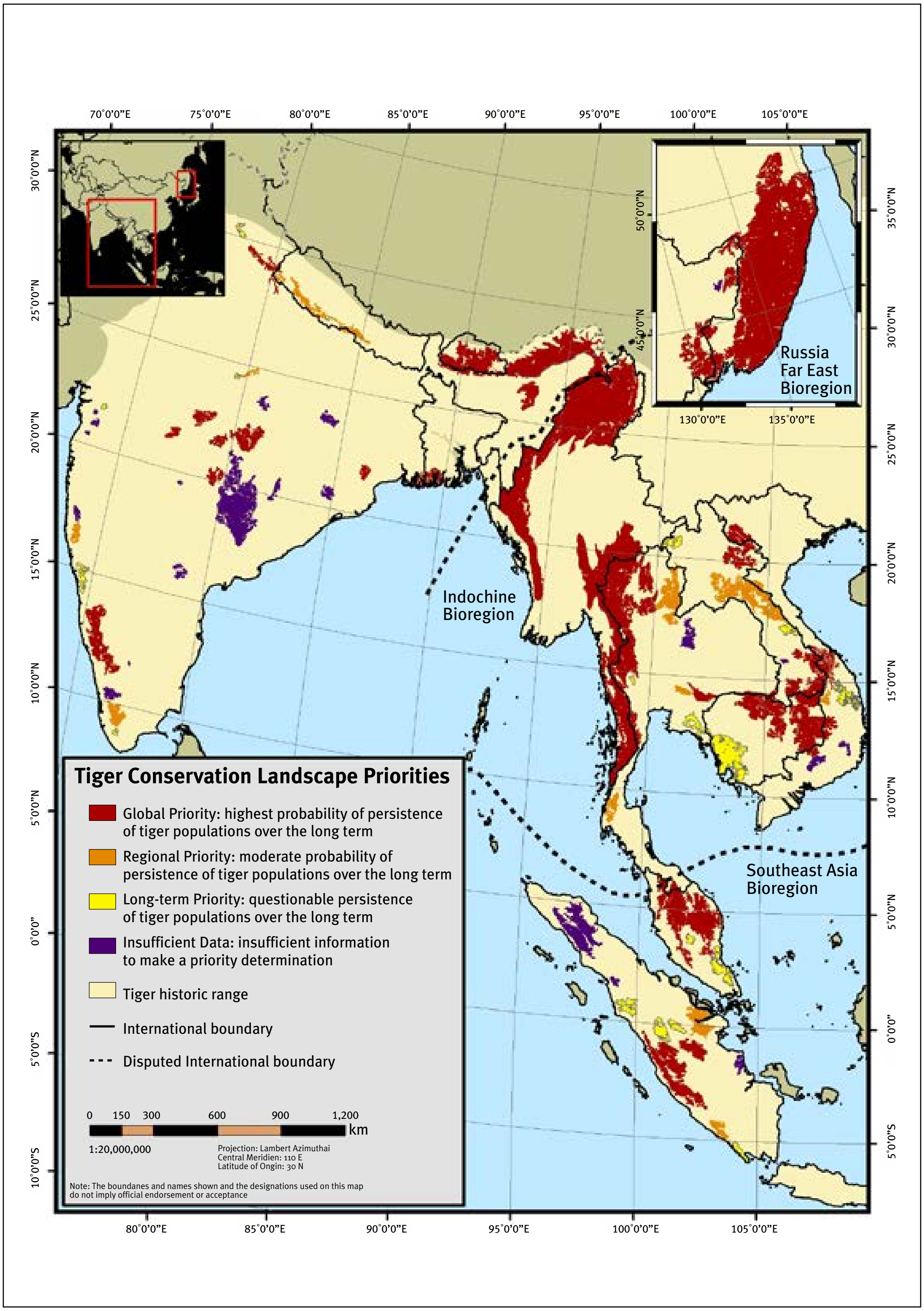


FIGURE 8.1 Tiger Conservation Landscapes Priorities. Sources: Dinerstein et al. 2006; Sanderson et al. 2006.

Case Study 8.1: Mapping Habitat for the Giant Panda in Sichuan Province, China

Authors: Jim Strittholt and Hong Jiang (Conservation Biology Institute)
Indicators: forest cover, fragmentation, threatened species
Potential monitoring scales: regional, national
Sensor: Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper (ETM+)
Imagery cost/hectare: free
Total project cost: $75,000
Limitations on accuracy: terrain shadows, cloud cover, important understory vegetation component

a. Introduction

Sichuan Province is located in southwest China and is recognized as one of the world's biodiversity hotspots. A wide range of natural environments occurs in the region, from alpine tundra to subtropical forests. The region supports high levels of species richness and centers of high species endemism. It is home to several of the world's best-known mammals, including the giant panda (*Ailuropoda melanoleuca*). The Sichuan Province also supports a growing human population that currently numbers nearly 90 million people. The intersection of globally significant biological values and high human pressures highlights this region as one of tremendous conservation importance, with considerable challenges. In response, the Chinese government has invested heavily over recent years to try to prevent the continuing degradation of natural ecosystems throughout the region, with special emphasis being paid to the giant panda—the symbol of the nation. Presently, there are 131 nature reserves, covering approximately 7,620,000 hectares (about 15.6 percent of the province), managed for conservation purposes to varying degrees. The purpose of this case study was to examine land cover change, fragmentation, and status of the giant panda for a large portion of its current range.

b. Methods

We used remote sensing (Landsat TM [1986] and Landsat ETM+ [2002]) to examine the major land cover changes, which we supplemented with a couple of important ancillary data layers (i.e., roads and bamboo distribution), as well as panda survey data for two dates: 1988 and 2004.

We processed Landsat 5 TM imagery (circa 1986) and Landsat 7 ETM+ imagery (circa 2002), using ERDAS Imagine software, and mapped general land cover types with special attention to native forests (the prime habitat for giant pandas), using an unsupervised classification approach we developed: the Optimal Iterative Unsupervised Classification (OIUC) method (Jiang et al. 2004). For approximately 30 percent of the study area, we collected more than 700 ground control points, using the global positioning system (GPS). The accuracy of the classification was assessed by field validation and a previously published ancillary spatial database.

c. Results

Results varied across the study area. For the northern portion, where commercial logging was halted in 1998, the loss of forest cover between the two sampling dates was significant, but less severe than in the southern portion, where commercial logging has continued at a rapid rate (figure 8.2). Liu et al. (2001) found similar results for the nearby Wolong Nature Reserve. Overall, image classification accuracy was estimated to be 92 percent for this region. The classification was correct 89 percent of the time for

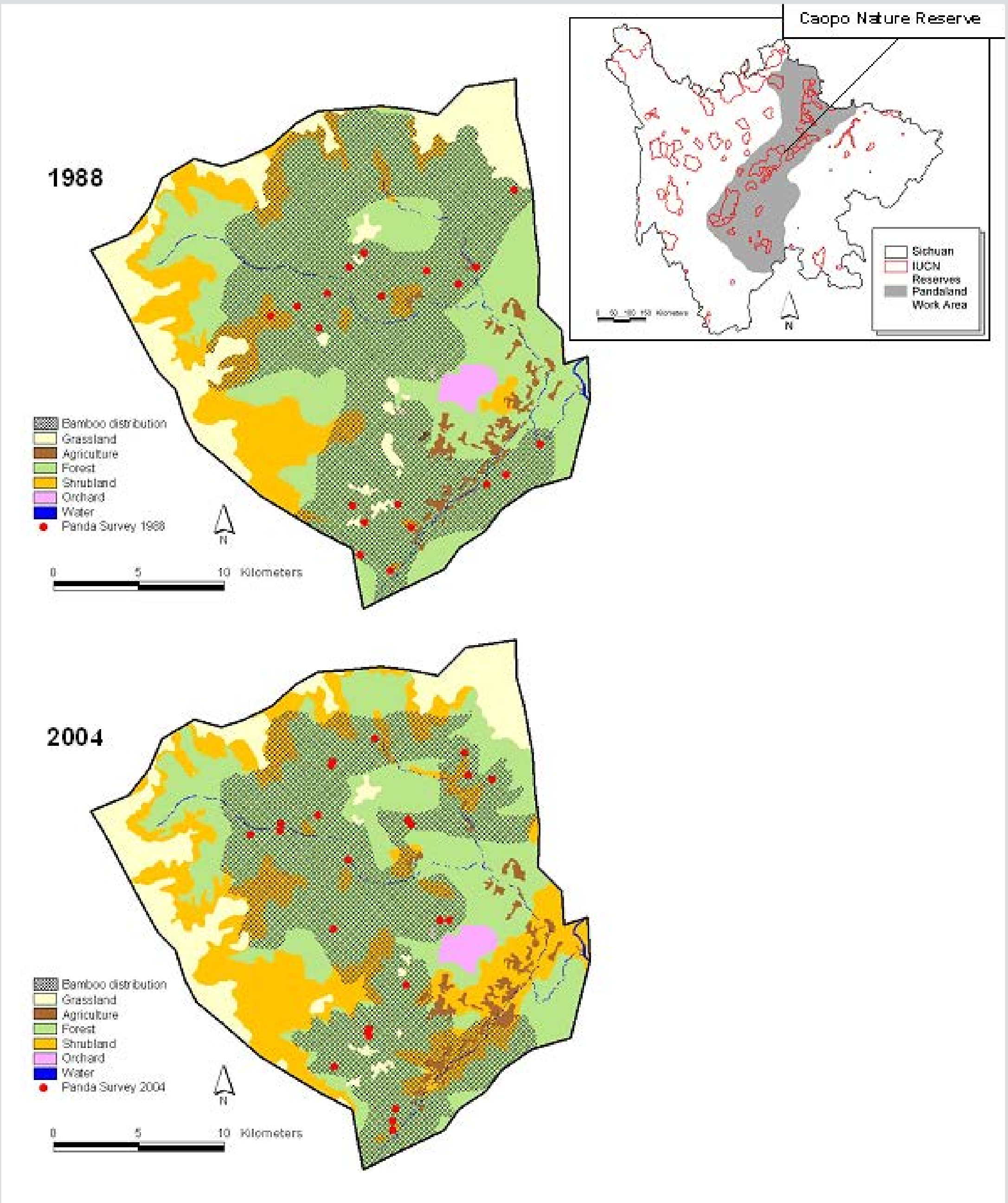


FIGURE 8.2 Changes in land cover, bamboo distribution, and giant panda locations for the Caopo Nature Reserve, 1988–2004.

forests, 85 percent for shrublands, 92 percent for orchards, 93 percent for grasslands, 90 percent for croplands, and 98 percent for water. Bamboo extent and spatial distribution were also variable. In the north, the natural life cycle of maturity, flowering, decline, and regeneration were the driving force for the observed changes. In the south, loss of bamboo was noted primarily because of human activity. Habitat fragmentation via roads and agriculture continues throughout the study area. Panda survey points for both dates were closely associated with bamboo cover. Overall, the newest panda survey shows greater numbers of pandas in 2004 than in the previous 1988 survey. There may be several explanations, including that greater effort was spent on the latest survey than in previous attempts.

For the Caopo Nature Reserve, difference in the number of pandas sampled between the two dates was not statistically significant, but there were some notable changes in the physical locations being used by the animals. For example, some regions have lost pandas (e.g., around the agricultural lands) between the two survey dates, which may coincide with either the loss of forest habitat around these agricultural lands or from direct disturbance by associated human presence and activity. It remains to be seen whether these lands will become unsuitable giant panda habitat in the future and to what degree habitat fragmentation will become a limiting factor, especially given that pandas are so closely linked with bamboo, which is so naturally dynamic in its distribution.

d. Limitations

The most important limitations in classifying satellite imagery for the mountains of southwest China include high levels of terrain shadows, cloud cover, and physical access for assessing accuracy. For our case study, the importance of mapping bamboo (an understory plant not easily discernable via remote sensing) was critical. Linderman et al. (2004) combined Landsat TM imagery and a nonlinear artificial neural network algorithm for mapping understory bamboo in the Wolong Nature Reserve and reported 80 percent accuracy. However, because we had to treat such a large area and field-based bamboo distribution maps were already available (including life-history stages: young, mature, flowering) for each of the survey years, we elected to convert the existing bamboo distribution maps (including life-history stages) for the two dates to computer-readable form by digitizing field maps. We were also very fortunate to acquire the national panda survey data results from 1988 and 2004 for all of Sichuan Province. Combining the necessary spatially explicit data on the changes in (1) forest habitat, (2) bamboo distribution, and (3) panda locations was extremely important for effective monitoring. Having this level of data for other species of concern around the world may be more challenging, but the importance of these multi-source data is an important finding.

8.5 Caveats

Inferring the number or distribution of species using a proxy (such as amount and configuration of habitat or primary productivity) assumes prior knowledge of species habitat preference. This information should be known with some degree of confidence before establishing a monitoring programme.

Even with complete knowledge of habitat preference, there is potential for over- or under-predicting the distribution of a species. For example, overestimating species range may occur if the remote sensing analysis predicts sufficient habitat for a given species, but in reality the species of interest is absent or limited for some other reason: perhaps lack of prey, disease, or poaching. The existence of multiple limiting factors, many of which cannot be remotely sensed, underscores the need to combine remote sensing analyses with on-the-ground surveys and local field knowledge.

Underestimation may occur when the remote sensing analysis either misclassifies the habitat or predicts the loss of habitat and therefore extirpation (local extinction) of a species—when the species is still present in reality. The likely cause of this error is that the definition of "habitat" for a species is too narrow, and that particular species is able to survive in a broader spectrum of habitats than originally known. Using a multistage sampling approach (i.e., employing remote sensing in conjunction with ground sampling) will help prevent this type of error. Again, the use of local knowledge—both when conducting ground surveys and when classifying imagery—is invaluable in minimizing this type of error.

Despite these shortcomings, remotely sensed mapping of habitat often provides a low-cost first approximation of the population status for many species. In addition, it can provide valuable information on how and where to survey for remaining populations of species. It represents a very powerful monitoring tool when employed together with finer-scale monitoring and field analysis.

8.6 Data and Other Resources

The following are examples of software specifically made for habitat modelling. Models can be constructed within a simple GIS as well.

MaxEnt: http://www.cs.princeton.edu/~schapire/maxent/

DivaGIS :http://research.cip.cgiar.org/confluence/display/divagis/Home;jsessionid=24956A8AE866D4124661AA06872D8B5B

GARP: http://nhm.ku.edu/desktopgarp/index.html

Biomapper: http://www2.unil.ch/biomapper/

8.7 References

Ancrenaz M., Gimenez O., Ambu L., Ancrenaz K. & Andau P. 2005. Aerial surveys give new estimates for orangutans in Sabah, Malaysia. PLoS Biology 3(1): www.plosbiology.org

Arrhenius, O. 1921. Species and Area. Journal of Ecology. 9:95-99.

Baillie J.E.M., Hilton-Taylor C. & Stuart S.N. 2004. 2004 IUCN Red List of Threatened Species. A Global Species Assessment. IUCN, Gland, Switzerland and Cambridge, U.K.

Best, P.B. 1990. Trends in the inshore right whale population off South Africa, 1969-1987. Marine Mammal Science 6: 93-108.

Buchanan, G., J. Pearce-Higgins, M. Grant, D. Robertson, and T. Waterhouse. 2005. Characterization of moorland vegetation and the prediction of bird abundance using remote sensing. J. Biogeography, 32: 697-707.

Dinerstein, E., C. Loucks, A. Heydlauff, E. Wikramanayake, G. Bryja, J. Forrest, J. Ginsberg, S. Klenzendorf, P. Leimgruber, T. O'Brien, E. Sanderson, J. Seidensticker, and M. Songer 2006. Setting Priorities for the Conservation and Recovery of Wild Tigers: 2005-2015. A User's Guide. WWF, WCS, Smithsonian and NFWF-STF, Washington, D.C, New York.

Henebry, G. M., & Merchant, J. W. 2002. Geospatial data in time: limits and prospects for predicting species occurrences. In Scott, J. M., Heglund, P. J., Morrison, M. L., Haufler, J. B., Raphael, M. G., Wall, W. A., & Samson, F. B. (Eds.), Predicting species occurrences: Issues of accuracy and scale. (pp. 291-302). Washington: Island Press.

Hochberg, E.J. and M.J. Atkinson. 2000. Spectral discrimination of coral reef benthic communities. Coral Reefs 19:164-171.

Gould.W. 2000 Remote Sensing of Vegetation, Plant Species Richness, and Regional Biodiversity Hotspots**.** *Ecological Applications*, 10, (6):1861-1870

Jiang Hong, J.R. Strittholt, P.A. Frost, and N.C. Slosser. 2004. The classification of late seral forests in the Pacific Northwest, USA using Landsat ETM+ imagery. Remote Sensing of Environment, 91:320-331.

Kerr, J.T. and M. Ostrovsky. 2003. From space to species: ecological applications for remote sensing. *Trends in* Ecology and Evolution, 18:299-305.

Key T., T.A. Warner, J.B. McGraw, and M.A. Fajvan. 2001. A Comparison of Multispectral and Multitemporal Information in High Spatial Resolution Imagery for Classification of Individual Tree Species in a Temperate Hardwood Forest. Remote Sensing of Environment 75: 100-113.

Koy, K., W. J. McShea, P. Leimgruber, B. N. Haack, and Myint Aung. 2005. Percent canopy cover using Landsat imagery to delineate habitat for Myanmar's endangered Eld's deer (*Cervus eldi*). Animal Conservation 8:289-296.

Leimgruber, P., C.A. Christen, A. Laborderie. 2005. The impact of Landsat satellite monitoring on conservation biology. Environmental Monitoring and Assessment 106: 81-101.

Liu, J., M. Linderman, Z. Ouyang, L. An, J. Yang, and H. Zhang. 2001. Ecological degradation in protected areas: the case of Wolong nature reserve for giant pandas. Science 292: 98-101.

Linderman, M., J. Liu, J. Qi, L. An, Z. Ouyang, J. Yang, and Y. Tan. 2004. Using artificial neural networks to map the spatial distribution of understory bamboo from remote sensing data. International Journal of Remote Sensing 25, 1685-1700.

Loh, J., R.E. Green, T. Ricketts, J. Lamoreux, M. Jenkins, V. Kapos, and J. Randers. 2005. Living Planet Index: using species population time series to track trends in biodiversity. Phil. Trans. R. Soc. B 360: 289-295.

Loucks, C.J., L. Zhi, E. Dinerstein, W. Dajun, F. Dali, and W. Hao. 2003. The giant pandas of the Qinling mountains, China: a case study in designing conservation landscapes for elevational migrants. Conservation Biology 17: 558-565.

Manley, P.N., W.J. Zielinski, M.D. Schlesinger, and S.R. Mori. 2004. Evaluation of multiple-species approach to monitoring species at the ecoregional scale. *Ecological Applications* 14: 296-310.

McGraw, J.B., T. A. Warner, T. L.Key, and W. L. Lamar. 1998. High spatial resolution remote sensing of forest trees. Trends in Ecology and Evolution 13: 300–301.

McShea, W. J., P. Leimgruber, Myint-Aung, S. L. Monfort., and C. Wemmer. 1999. Range collapse of a tropical cervid (*Cervus eldi*) and the extent of remaining habitat in Central Myanmar. Animal Conservation 2:173-183.

Milner-Gulland, E.J., M.V. Kholodova, A. Bekenov, O. Bukreeva, I.A. Grachev, L. Amgalan, and A.A. Lushchekina. 2001. Dramatic declines in saiga antelope populations. Oryx 35: 340-345.

Mumby, P.J., E.P. Green, A.J. Edwards, and C.D. Clark. 1997. Coral reef habitat mapping: how much detail can remote sensing provide? Marine Biology 130:193-202.

Murn, C., M.D. Anderson, and A. Anthony. 2002. Aerial survey of African white-backed vulture colonies around Kimberley, Northern Cape and Free State provinces, South Africa. South African Journal of Wildlife Research 32:145-152.

Osborne, P.E., J.C. Alonso, and R.G. Bryant. 2001. Modeling landscape-scale habitat use using GIS and remote sensing: a case study with great bustards. J. Applied Ecology 38:458-471.

Raxworthy, Christopher J., Enrique Martinez-Meyer, Ned Horning, Ronald A. Nussbaum, Gregory E. Schneider, Miguel A. Ortega-Huerta & A. Townsend Peterson. 2003. Predicting distributions of known and unknown reptile species in Madagascar. Nature 426: 837-841.

Rushton, S.P., S.J. Ormerod, and G. Kerby. 2004. New paradigms for modeling species distributions? J. Applied Ecology, 41: 193-200.

Sanderson, E., J. Forrest, C. Loucks, J. Ginsberg, E. Dinerstein, J. Seidensticker, P. Leimgruber, M. Songer, A. Heydlauff, T. O'Brien, G. Bryja, S. Klenzendorf, and E. Wikramanayake 2006. Setting Priorities for the Conservation and Recovery of Wild Tigers: 2005-2015. The Technical Assessment. WCS, WWF, Smithsonian, NFWF-STF, New York – Washington, D.C.

Sauer, J. R., J. E. Hines, and J. Fallon. 2005. The North American Breeding Bird Survey, Results and Analysis *1966 – 2004. Version 2005.2.* USGS Patuxent Wildlife Research Center, Laurel, MD. http://www.mbr-pwrc.usgs.gov/bbs/bbs.html (accessed January 2007)

Sidle, J.G., D.H. Johnson, and B.R. Euliss. 2001. Estimated areal extent of colonies of black-tailed prairie dogs in the northern Great Plains. J. Mammology 82: 928-936.

Stauffer, D. F. 2002. Linking populations and habitats: Where have we been? Where are we going? In Scott, J. M., Heglund, P. J., Morrison, M. L., Haufler, J. B., Raphael, M. G., Wall, W. A., & Samson, F. B. (Eds.), Predicting species occurrences: Issues of accuracy and scale (pp. 53-61). Washington: Island Press.

Tracey, J.P., P.J.S. Fleming and G.J. Melville. 2005. Does variable probability of detection compromise the use of indices in aerial surveys of medium-sized mammals? Wildlife Research 32(3) 245–252.

Turner, W., S. Spector, N. Gardiner, M. Fladeland, E. Sterling, and M. Steininger. 2003. Remote sensing in biodiversity science and conservation. Trends in Ecology and Evolution 18(6): 306-314.

Whitehouse, A.M., A.J. Hall-Martin, and M.H. Knight. 2001. A comparison of methods used to count the elephant population of the Addo Elephant National Park, South Africa. African Journal of Ecology 39: 140-145.

Chapter 9. Coverage of Protected Areas

AUTHOR: James Strittholt[1]
CONTRIBUTOR: Peter Leimgruber[2]
REVIEWERS: Gary Geller[3], Sarat Babu Gidda[4]

1 Conservation Biology Institute, 2 Smithsonian National Zoological Park, 3 NASA Jet Propulsion Laboratory, 4 Secretariat of the Convention on Biological Diversity

Remote sensing based indicators for protected areas:

- Area of protected areas
- Size distribution of protected areas
- Representation of protected areas
- Isolation of protected areas
- Landscape condition adjacent to protected areas
- Levels of encroachment on, or degradation of, protected areas

9.1 Background

The protected area network (national parks, nature reserves, and other designations) is widely recognized as a crucial tool for protecting global biodiversity; maintaining environmental services; and protecting cultural, aesthetic, and ethical values (Hockings et al. 2000). According to Article 2 of the Convention on Biological Diversity (CBD), a protected area is "a geographically defined area which is designated or regulated and managed to achieve specific conservation objectives" (CBD 1992). Similarly, the World Conservation Union (IUCN) defines protected areas as "areas of land and/or sea especially dedicated to the protection and maintenance of biological diversity, and of natural and associated cultural resources, and managed through legal or other effective means" (IUCN 1994). The IUCN World Commission on Protected Areas (WCPA) protected area categories are listed in Box 9.1. This system for classifying areas by management objective is viewed as the global standard.

Depending on local context, protected areas are faced with a variety of pressures or threats. Some are primarily threatened by human encroachment, others by invasive species, while others are well protected, but isolated from other natural habitats. Many protected areas are faced with multiple stressors. Most extrinsic pressures (e.g., extreme disturbance events or climate change) are very difficult to manage. Some of the more intrinsic ones (e.g., exotic species invasion or degradation by human visitation) can be managed more effectively provided that the managers of the protected areas have enough financial resources and human capacity to address these stressors (Bruner et al. 2004).

The WCPA has produced a framework for assessing the effectiveness of protected area management (Hockings et al. 2006). Effectiveness monitoring can be approached by measuring trends in status in the context of the site's management history and by comparing changes within the protected area with changes in nearby similar ecosystems. Assessment criteria for the protected area status include biological significance, threat, vulnerability, and national context. Many of these can be assessed using techniques outlined in this sourcebook, with the following caveat: an area whose condition has declined may currently be well managed, but there may be a lag between improved management practices and visible improvement in condition.

One of the first steps in evaluating protected area status is to identify its/their location(s). The collation of accurate, spatially explicit data on protected areas can be technically and politically challenging. In the worst-case scenario, a given area may lack precise spatial definitions in law or demarcation on the ground.

In some countries, a designated area does not enjoy full legal status until demarcation is carried out.

The World Database of Protected Areas (WDPA), managed at the United Nations Environment Programme World Conservation Monitoring Centre (UNEP-WCMC) in collaboration with the World Database on Protected Areas Consortium, compiles information on the status, environment, and intended management of individual protected areas, including location data. Updates are published annually, and the recorded year of designation, area, and category of each site can be used to summarize trends through time (WDPA Consortium 2005). WDPA is currently finalizing new protected areas system design specifications to improve completeness and accuracy of this ever-changing data theme. The WDPA database is the best available tool for understanding the distribution and extent of protected areas on a global scale, but for individual countries, national data may be more up-to-date and complete at this time.

BOX 9.1 IUCN Protected Area Management Categories. Source: IUCN 1994.

Category Ia:	Strict Nature Reserve: protected area managed mainly for science.
Category Ib:	Wilderness Area: protected area managed mainly for wilderness protection.
Category II:	National Park: protected area managed mainly for ecosystem protection and recreation.
Category III:	Natural Monument: protected area managed mainly for conservation of specific natural features.
Category IV:	Habitat/Species Management Area: protected area managed mainly for conservation through management intervention.
Category V:	Protected Landscape/Seascape: protected area managed mainly for landscape/seascape conservation and recreation.
Category VI:	Managed Resource Protected Area: protected area managed mainly for the sustainable use of natural ecosystems.

9.2 Protected Area Network Development

While the extent of a protected area network can be monitored without recourse to remote sensing, remote sensing data can assist in the planning of an expanded network. Such expansion has been recommended both by protected area professionals and by the Conference of the Parties (COP) to the CBD. The Durban Action Plan (WCPA 2004) emerged from the Fifth IUCN World Parks Congress in 2003, a meeting of protected area professionals participating in the World Commission on Protected Areas. The fourth main target of this plan is, "A system of protected areas representing all the world's ecosystems is in place by the time of the next World Parks Congress." Among other points, the plan proposes that quantitative targets be set for each ecosystem by 2008, and that all Red List species are protected in situ, with priority given to critically endangered species confined to single sites.

In February 2004, CBD COP 7 adopted Decision VII/28 on protected areas, which includes an annexed Programme of Work (CBD 2004). The Programme of Work will be assessed at each COP until 2010 and has the overall objective of "the establishment and maintenance by 2010 for terrestrial and by

2012 for marine areas of comprehensive, effectively managed, and ecologically representative national and regional systems of protected areas that collectively, inter alia through a global network contribute to achieving the three objectives of the Convention and the 2010 target to significantly reduce the current rate of biodiversity loss."

The Decision requests individual countries to "elaborate outcome-oriented targets for the extent, representativeness and effectiveness of their national systems of protected areas." The Programme of Work suggests that Parties complete gap analyses and establish protected area targets by 2006. Decision VII/30 of COP 7 provides a global context, specifying a provisional goal of protection of at least 10 percent of each of the world's ecological regions.

At a system level, a gap analysis considers the representation of ecosystems or species of conservation interest within the existing protected area network (Scott and Schipper 2006). It may present one or more alternative solutions for modifications to the network to increase their representation. In addition, isolation of protected areas may be addressed by linking them through ecological corridors, such as the Mesoamerican Biological Corridor (www.fauna-flora.org/americas/mbc.html) and the Pan-European Ecological Network (www.coe.int/t/e/cultural_cooperation/environment/nature_and_biological_diversity/ecological_networks/PEEN/). Any allocation of new protected areas relies upon multicriteria decision-making and so requires consistent information on biodiversity value, threats, and constraints such as existing land use. A considerable amount of effort has been focused on methods of maximizing the biodiversity represented within the minimum area, at both a network level and an individual site level. More recently, methods for assessing the impacts of climate change have been explored (Araújo et al. 2004). Maps of status and trends in extent of biomes, derived from remote sensing, provide one important input to such analyses. Additional biodiversity data may already be available at a national scale or be sourced from international data sets such as those collated for the Global Amphibian and Mammal Assessments and the Millennium Ecosystem Assessment.

9.3 Potential Role for Remote Sensing

Remote sensing can play only a very limited role in mapping designated protected areas. Its main and important function is in appraising protected area condition, including the condition of surrounding land. By measuring the biophysical conditions (principally land cover types and human disturbance, including local and regional habitat fragmentation), remote sensing can be useful in assessing management effectiveness of protected areas. Indicators for monitoring protected area status can therefore be derived by spatial overlay of themes such as land cover change (inside and outside protected area boundaries) and various human disturbance layers with the national protected area boundary theme.

At a global scale, remote sensing data have been used to obtain an overview of habitat integrity and degree of conversion within and around protected areas (Defries et al. 2005; Hoekstra et al. 2005). In some countries, a protected areas monitoring system is already in place and may include a strong remote sensing component. In other cases, the emphasis has been on more ad hoc project work. Numerous studies of protected area status and condition have used remote sensing technology (Bock et al. 2005; Curran et al. 2004; Rand 2002; Salami et al. 1999; Vasconcelos et al. 2002). Future coordination of these efforts could provide a powerful monitoring resource as efforts to evaluate overall protected area effectiveness are developed and implemented (Dudley et al. 1999; Courrau 1999; Hockings 2003; Parish et al. 2003).

"Watchful eye" monitoring looks for obvious visual changes in time series of remote sensing images. For example, repeat analysis of satellite imagery for World Heritage sites is being carried out with the support of the European Space Agency, starting with the mountain gorilla habitat of the Virunga Mountains (see http://www.cotf.edu/ete/modules/mgorilla/mgvirungas.html and UNESCO 2005). Remote sensing can provide a "coarse filter" or "alarm," highlighting target areas for more detailed examination (Townshend et al. 2002; Zhan et al. 2002). Protected area monitoring may also be more sophisticated, extracting specific, quantitative indicators.

Multiple studies have been devoted to assessing the role of remote sensing in indicating the location, extent, rate, and sometimes even drivers of changes in and around protected areas (Liu et al. 2001; Sánchez-Azofeifa et al. 2001; Sánchez-Azofeifa 2003). Not only can remote sensing be used to monitor protected area condition, but it can also be used to identify locations outside protected area boundaries that may be better suited for natural resource extraction; however, these findings would require field validation of both suitability and long-term conservation impacts (Kairo et al. 2002). These studies demonstrate that remote sensing alone is not enough to answer every question pertaining to protected area monitoring, but it is an extremely important data resource (as demonstrated in the figures below).

An important source of multitemporal imagery focused on many of the world's protected areas is TerraLook (formerly known as the Protected Areas Archive), a project of the NASA Jet Propulsion Lab (http://asterweb.jpl.nasa.gov/TerraLook.asp). The examples below illustrate the use of remote sensing to address a range of issues in and around protected areas. (These examples were generously provided by TerraLook.)

A land cover change example from TerraLook found in figure 9.1, which shows the Iguazú Falls National Parks in Argentina and Brazil. The satellite image on the left was acquired in 1975 and the one on the right in 2001. Major changes have taken place over the 26-year period, both inside and outside the park, including: (1) the construction of the Itaipu Dam on the Paraná River and its resulting large reservoir (top of right image); (2) the sprawl of the twin cities of Ciudad del Este and Foz do Iguazú (left center, just above the intersection of the Iguazú and Paraná rivers); (3) widespread conversion of natural land cover to agriculture; and (4) some return of forest cover along the Brazilian side of the park, north of the Iguazú River.

Figure 9.2 focuses on the northern border of the Dong Hua Sao Reserved Forest in southern Lao People's Democratic Republic (PDR). In the time series presented (1975, 1989, and 2000), a wave of agricultural encroachment can be seen. The reserve managers knew that some encroachment by coffee farmers might be taking place within this relatively remote portion of the protected area, but they were surprised by the extent of the land cover change shown in the imagery. This imagery also provides an excellent example of the importance of field validation. By the latest image, some apparent recovery from

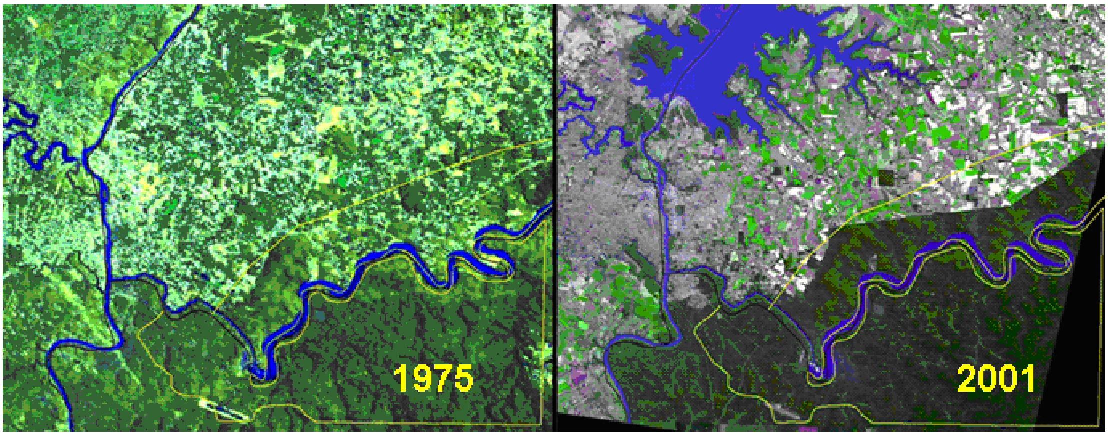


FIGURE 9.1 Iguazú Falls National Parks in Argentina and Brazil (outlined in yellow, bottom right of images). Gray tones depict development, light green and white depict agriculture, blue water, and dark green forest. (Images are the courtesy of TerraLook.)

FIGURE 9.2 Agricultural encroachment into the northern sector of Dong Hua Sao Reserved Forest in southern Lao PDR. The darker green areas are generally intact forest, and the lighter green and brown patches are disturbed forest or agriculture. The red arrow shows area of apparent recovery since disturbance during the 1980s. (Images are the courtesy of the TerraLook.)

disturbance is observed (marked with a red arrow). The forest canopy has closed here, but it is not clear whether the canopy is formed by coffee bushes or native forest species.

Finally, figure 9.3 shows two images of Kaziranga National Park in northeast India. The northern edge of the park border lies along the dynamic border of the Brahmaputra River. The dynamic nature of this river, redistributing sediment and altering channels, provides an interesting management challenge. These images from 1973 and 2001 illustrate erosion and deposition patterns that have occurred during this period: the river bank has receded by nearly 2 kilometres in one area and accreted by nearly 3 kilometres in another.

While these examples are mostly visual, the information contained in them can be turned into quantitative indicators. This type of imagery can be used to quantify trends in land cover change, habitat fragmentation, and changes in habitat of selected species. Table 9.1 lists a selection of protected area monitoring issues with which remote sensing can assist. Indeed, remote sensing is sometimes the only effective way to assess a particular issue.

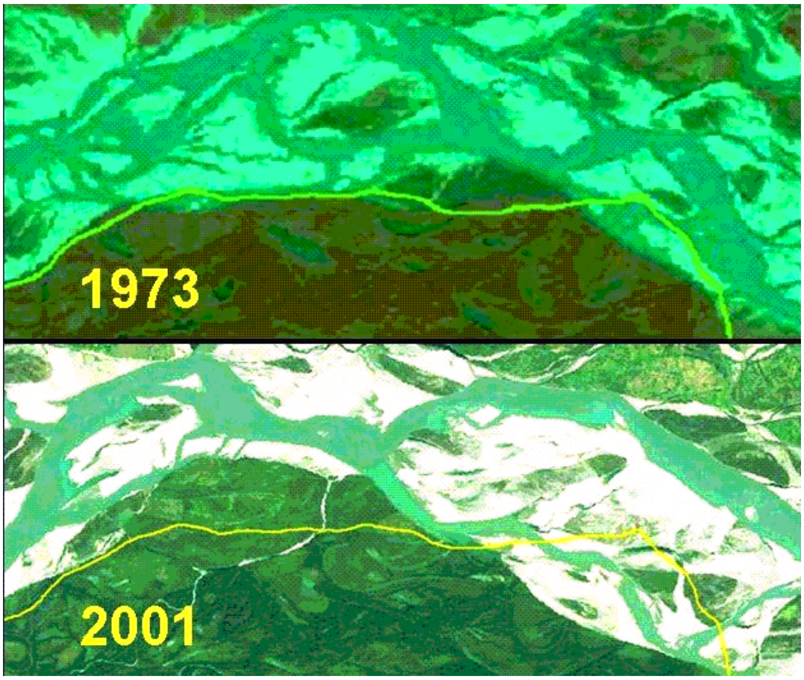


FIGURE 9.3 Shifting edge of the Brahmaputra River on the north side of Kaziranga National Park, India. (Images are the courtesy of TerraLook.)

TABLE 9.1 Potential roles for remote sensing in monitoring of protected areas.

Focus of monitoring	Potential role of remote sensing
Land cover change and encroachment	Monitor illegal encroachment on protected areas and any other agriculture, development, and resource extraction in and around protected areas
Infrastructure development	Help to minimize impact of road expansion and any other permitted developments within protected areas
Habitat fragmentation	Identify, quantify, and monitor habitat of surrounding area; where feasible, identify fragmentation metrics relevant to target species or ecosystem
Livestock grazing	Monitor "greenness index" or some other indicator of grazing pressure and range condition
Invasive species	Identify (possibly), map, and monitor distribution of invasives; track related changes in seral stages (development stages of ecological communities) and loss of aquatic habitat
Special habitat	Monitor habitat area for threatened species
Plant succession	Monitor natural plant community succession after natural or anthropogenic disturbance
Recurring drought, catchment area changes, erratic release of water	Monitor alteration in habitats and invasion of woodland in wetland
Fire	Identify, map, and document extent of burns; map seral stages of the habitat; MODIS Rapid Response alert system; fire history; burn mapping
Contamination of water with pesticides, fertilizers, sediment, etc.	Monitor agricultural practices and land use pattern in catchment areas
Pollution	Monitor location and movement
Erosion	Identify, map, and monitor riverbank position
Diseases and pests	Habitat and vector modelling and prediction (advanced)
Climate change	Monitor land area of low-lying islands; quantify coral bleaching extent in MPAs

Case study 9.1: Monitoring Land Cover Change in Myanmar's Protected Areas

Author: Peter Leimgruber
Indicator: forest cover extent and change
Potential monitoring scales: landscapes, small and large nations, global
Sensor: Landsat TM and Landsat ETM+
Imagery cost: free from Internet sites, or up to $600/image from United States Geological Survey (USGS). An orthorectified Landsat data set can be downloaded for free from Global Land Cover Facility at the University of Maryland.
Limitations on accuracy: cloud cover, confusion of forest canopy phenology with human-induced change and vice versa, inaccuracy in protected areas maps.

a. Introduction

Myanmar is one of the most forested countries in mainland Southeast Asia. These forests support a large number of important species and endemics and represent the last strongholds for species such as tiger (*Panthera tigris*), Asian elephant (*Elephas maximus*), Gurney's pitta (*Pitta gurneyi*), and Eld's deer (*Cervus eldi*). Indo-Burman forests are considered a biodiversity hotspot, and protection of representative ecosystems in this region is a priority for global biodiversity conservation. Since 1985, the number of protected areas in Myanmar has increased from 14 to 33. Some analysts estimate current protection to encompass little more than 2 percent of Myanmar's total land area. Limited resources, personnel, and infrastructure are thought to have limited the effectiveness of many of Myanmar's parks. A recent countrywide assessment of forest cover and forest cover change conducted by the Smithsonian Institution, based on 1990 and 2000 Landsat images, shows that forest cover has been in slow decline. However, the Smithsonian Institution has identified 10 deforestation hotspots. Most notable were the losses of mangrove forests and dry forests in the central regions of the country. The effectiveness of protected areas in preventing deforestation was assessed using the same methods.

b. Methods

Complete coverage of Landsat 5 Thematic Mapper (TM) images for 1989–1992 and Landsat 7 Enhanced Thematic Mapper (ETM+) images for 2000–2001, was acquired for all terrestrial protected areas in Myanmar. All images were registered to NASA's Geocover, a set of orthorectified images from the 1990s. All of the selected images had been acquired at the end of the monsoon season and the beginning of the dry season, when forest vegetation tends to be lush and cloud cover is low. These factors reduced the confounding effects of seasonal changes in leaf cover in the country's mixed-deciduous and dry forests. Cloud cover among images used in the analysis was less than 2 percent.

To determine changes in the forest cover of protected areas between 1990 and 2000, an iterative supervised classification technique was used. This integrates multitemporal images and classifies forest cover and forest cover changes in one step. Satellite images acquired during the same seasons in different years are combined into one data set and used in supervised classification. During classification, the analyst identifies homogenous areas of forest cover and forest cover change and derives spectral response statistics for these areas. Based on the spectral responses, the images are then classified into maps depicting forest cover and deforestation. Classification categories were defined as follows:

(1) Nonchange classes: (a) Forest. All closed-canopy tall forests (canopy cover greater than 50 percent; tree height greater than 5 metres [16.4 feet]) observed on both image dates, including most mature forests; also savannahlike dry dipterocarp forests and sometimes forests partially degraded by selective logging or thinning. (b) Water. All water bodies such as oceans, lakes, reservoirs, rivers, and wetlands observed in the ~2000 imagery. (c) Nonforest. All areas that were neither classified as water nor as forest in the ~1990 imagery. (d) No data. All areas obscured by clouds, cloud shadow, and other shadow in one of the satellite images.

(2) Change classes: (a) Deforestation. All areas observed as forest in ~1990 and nonforest in ~2000. (b) Reforestation. All areas observed as nonforest in ~1990 and secondary forest in ~2000. (c) Water change. All areas changing from water to nonwater or vice versa.

c. Results

Myanmar has 24 protected areas that are larger than 100 square kilometres and have more than 40 percent forest cover. Several of these protected areas (n=6) were created before independence from British rule in 1948, but a large number were established after the Nature Conservation and National Parks Project funded by FAO-UNDP in 1983. An almost equal number (n=8) are proposed and may be gazetted in the next few years.

Our satellite analysis of remaining forest cover and forest cover conversion revealed that most protected areas still have substantial forest cover, frequently above 90 percent. Several areas have as little as 42 percent forest cover. Annual deforestation rates inside the protected areas generally are below the countrywide average of 0.2 percent, but several areas have higher losses, especially Pidaung, Kahilu, Panlaung-Pyadalin Cave, and Shwe-U-Daung (Figure 9.4). Three of these areas are among the oldest protected areas of the country, indicating that protection over longer time periods may be only moderately successful or that there is a more effective level of conservation planning for newer areas.

Deforestation pressures, measured as the deforestation rate within 5 kilometres of the protected area boundary, are severe for several protected areas, with annual rates well above the countrywide average. These include Pidaung, Shwe-U-Daung, Chatthin, and Meinmahla Kyun (Figure 9.4). In the first two, these pressures have already led to forest loss inside the protected areas, while in the last two, deforestation on the inside was minimal over the study period. In the case of Chatthin, this may be explained by the presence of an international conservation project to preserve endangered Eld's deer and a well-trained protected area staff. However, Meinmahla Kyun has only recently been gazetted and has few staff. Lack of deforestation inside this area may result from low accessibility.

Overall, Myanmar's protected areas currently seem to effectively protect closed-canopy forests. Some of the oldest areas have undergone the most deforestation over the 10-year period, but Htamanthi, declared in 1974, has experienced no forest loss. Most of the areas have a low ratio of inside to outside deforestation, indicating that even where pressures outside the park are high, protected areas are often extremely effective.

d. Limitations

Using multi-date Landsat images to assess remaining forest cover and forest cover changes in protected areas is a useful and cost-effective analysis to identify problem areas. However, the techniques have several limitations:

To address progress toward the CBD 2010 target, it would be necessary to assess whether there is a *reduction in the rate of change* in natural forest cover within protected areas. This would require imagery from more than two dates.

In addition, 10 years are a short time span over which to evaluate the effectiveness of a protected area. We suggest that longer-term monitoring systems be employed that reach back to the 1980s and map forests in protected areas at five-year intervals.

A significant portion of the closed canopies mapped in our study may have been secondary forest. The extent of this issue can only be evaluated via extensive ground-truthing.

The empty-forest problem: Commercial trade as well as subsistence hunting can severely reduce species diversity, even in structurally intact natural forests. Remote sensing and satellite imagery cannot provide a direct measure of these threats and their effect on biodiversity.

Monitoring the extent of some habitats (e.g., wetlands, natural grasslands) using Landsat satellite imagery is more difficult than is monitoring forest extent.

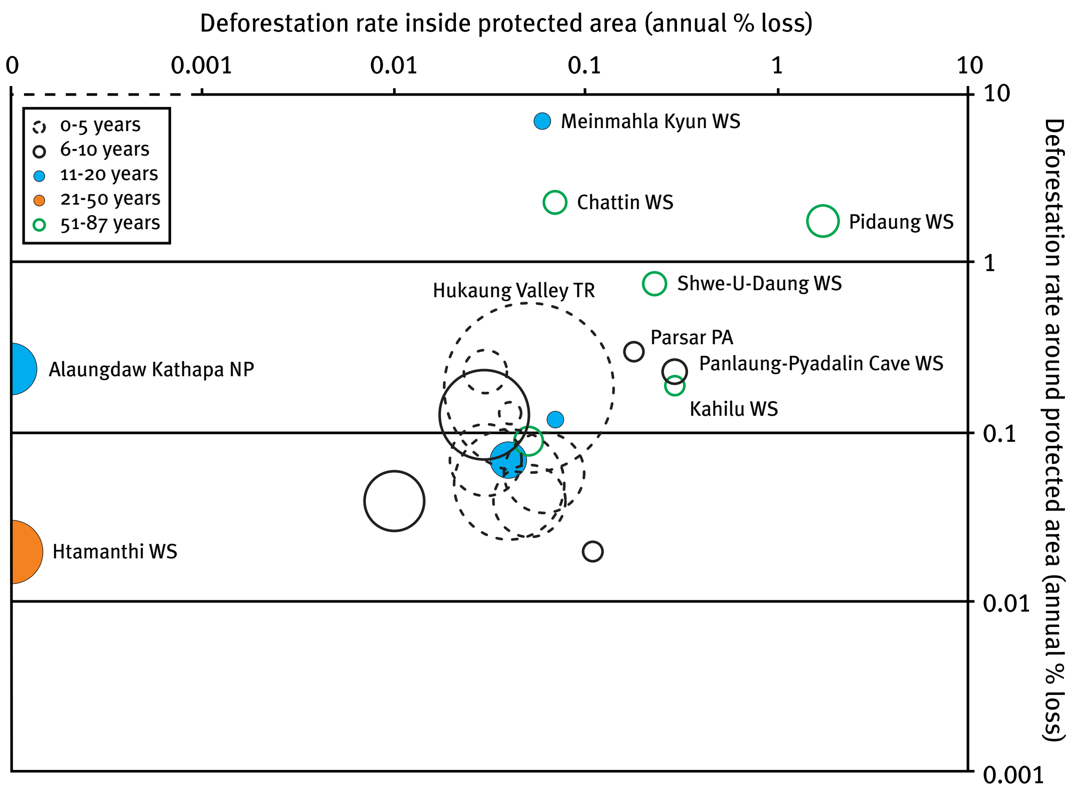


FIGURE 9.4 Deforestation rates inside and surrounding protected areas by age and size, Myanmar. Bubble area is scaled to protected area size (maximum = 15,626 square kilometers, minimum = 129 square kilometres. Selected protected area names and designations shown (NP = National Park, PA = Protected Area, TR = Tiger Reserve, WS = Wildlife Sanctuary). The figure demonstrates that older and smaller parks are more likely to be affected by deforestation inside and on the outside. New and large parks tend to be much less affected by deforestation. Parks above the diagonal line have lower deforestation on the inside than the outside, indicating that they are better at withstanding deforestation pressures.

9.4 Data and Other Resources

The World Database on Protected Areas (WDPA)

This is the most comprehensive dataset on protected areas worldwide and is managed by UNEP-WCMC in partnership with the IUCN World Commission on Protected Areas (WCPA) and the World Database on Protected Areas Consortium. The WDPA is an extensive relational database containing information on the status, environment and management of individual protected areas. The web sites listed below allow query of the database, exploration of the spatial data through an interactive map service, and download of the latest release of the database. Various publications are also available for download.
http://www.unep-wcmc.org/wdpa/index.htm and http://www.unep-wcmc.org/protected_areas

Terra Look

Formerly known as the Protected Area Archive (PAA), TerraLook distributes collections of satellite images packaged with simple visualization and analysis tools. The images to be included in a collection can be selected by users from a global archive, or a user can obtain one of the "stock" collections. The viewer/toolkit, which is bundled with the image collection, provides simple and intuitive capabilities to allow users to display protected area boundaries and other GIS shape files on the image, adjust and annotate the image so it can be used as a communication vehicle, measure area and distance on the image, compare images taken at different times, and perform other activities useful for conservation.
http://asterweb.jpl.nasa.gov/TerraLook.asp

Protected Areas Learning Network (PALNet)

PALNet aims to compile and disseminate protected area management knowledge, with an additional focus on the implications of global change. The large number of documents and project profiles available on the site can be searched or browsed by category.
http://www.parksnet.org

9.5 References

Araújo, M.B., M. Cabeza, W. Thuiller, L. Hannah, and P.H. Williams. 2004. Would climate change drive species out of reserves? An assessment of existing reserve-selection methods. Global Change Biology 10(9):1618-1626.

Bock, M., P. Xofis, J. Mitchley, G. Rossner, and M. Wissen. 2005. Object-oriented methods for habitat mapping at multiple scales – Case studies from Northern Germany and Wye Downs, UK. Journal for Nature Conservation 13(2-3):75-89.

Bruner, A.G., R.E. Gullison, and A. Balmford. 2004. Financial costs and shortfalls of managing and expanding protected-area systems in developing countries. BioScience 54(12): 1119 — 1126.

CBD. 1992. The Convention on Biological Diversity. http://www.cbd.int/convention/default.shtml (accessed May 22, 2007).

CBD. 2004. Programme of Work on Protected Areas. Annex to Decision VII/28: Protected areas. Decisions Adopted by the Conference of the Parties to the Convention on Biological Diversity at its Seventh Meeting. UNEP/CBD/COP/7/21. http://www.cbd.int/doc/decisions/COP-07-dec-en.pdf (accessed May 22, 2007).

Courrau, J. 1999. Monitoring protected area management in Central America: A regional approach. Parks 9 :56-60.

Curran, L., S. Trigg, A. McDonald, D. Astiani, Y. Hardiono, P. Siregar, I. Caniagon, and E. Kasischke. 2004. Lowland forest loss in protected areas of Indonesian Borneo. Science 303(5660): 1000-1003.

Defries, R., A. Hansen, A.C. Newton, and M.C. Hansen. 2005. Increasing isolation of protected areas in tropical forests over the past twenty years. Ecological Applications 15(1): 19-26.

Dudley, N., M. Hockings, and S. Stolton. 1999. Measuring the effectiveness of protected area management.

Partnerships for Protection. Eds. S. Stolton, and N. Dudley. London: Earthscan, 249-257.

Hockings, M. 2003. Systems for Assessing the Effectiveness of Management in Protected Areas. Bioscience 53 (9): 828-832.

Hockings, M., Stolton, S. and N. Dudley. 2000. Evaluating Effectiveness: A Framework for Assessing the Management of Protected Areas. Gland, Switzerland and Cambridge, UK., IUCN.

Hockings, M, S Stolton, F Leverington, N Dudley and J Corrau 2006. Evaluating effectiveness : A framework for assessing management effectiveness of protected areas 2nd edition, IUCN WCPA and University of Queensland, Gland Switzerland and Brisbane Australia.

Hoekstra, J.M., T.M. Boucher, T.H. Ricketts, and C. Roberts. 2005. Confronting a biome crisis: Global disparities in habitat loss and protection. Ecology Letters 8: 23-29.

IUCN. Guidelines for protected areas management categories. IUCN World Commission on Protected Areas with the assistance of the World Conservation Monitoring Centre. 1994. Cambridge, UK and Gland, Switzerland. http://www.unep-wcmc.org/protected_areas/categories/eng/index.html. (accessed December 2005).

Kairo, J.G., B. Kivyatu, and N. Koedam. 2002. Application of remote sensing and GIS in the management of mangrove forests within and adjacent to Kiunga Marine Protected Area, Lamu, Kenya. Environment, Development and Sustainability 4 (2): 153–166.

Liu, J., M. Linderman, Z. Ouyang, L. An, J. Yang, and H. Zhang. 2001. Ecological degradation in protected areas: The case of Wolong Nature Reserve for Giant Pandas. Science 292 (5514):98-101.

Parrish, J.D., D.P. Braun, and R.S. Unnasch. 2003.Are we conserving what we say we are? Measuring ecological integrity within protected areas. Bioscience 53 (9): 851-860.

Rand, D. Forest fragmentation near Tai National Park, Ivory Coast. PAMS department, University of Canterbury, Christchurch, New Zealand, 2002. http://www.cybermagic.co.nz/resources/content/20010822.htm. (December 2005).

Salami, A.T., O. Ekanade, and R.O. Oyinloye. 1999. Detection of forest reserve incursion in south-western Nigeria from a combination of multi-date aerial photographs and high resolution satellite imagery. International Journal of Remote Sensing 20(8):1487-1497.

Sánchez-Azofeifa, G.A., G.C. Daily, A. Pfaff, and C. Busch. 2003. Integrity and isolation of Costa Rica's national parks and biological reserves: examining the dynamics of land-cover change. Biological Conservation 109:123-135.

Sánchez-Azofeifa, G.A., R.C. Harriss, and D.L. Skole. 2001. Deforestation in Costa Rica: A quantitative analysis using remote sensing imagery. Biotropica 33(3):378-384.

Scott, J.M., and J. Schipper. 2006. Gap analysis: a spatial tool for conservation planning. Principles of Conservation Biology Comp. M.J. Groom, G.K. Meffe, and C. Ronald Carroll. Sunderland, MA: Sinauer. 518-519.

Townshend, J.R.G., R.S. DeFries, X. Zhan, R.A. Sohlberg, M. C. Hansen, C. DiMiceli, M.L. Carroll, and J.C. Eastman. 2002. MODIS 250m and 500m time series data for change detection and continuous representation of vegetation characteristics. Analysis of multi-temporal remote sensing images; Proceedings of the First International Workshop on the Analysis of Multi-temporal Remote Sensing 2001, Trento, Italy. Eds. L. Bruzzone, and P. Smits. World Scientific, London, UK. 233–40.

Vasconcelos, M., J. Mussa, A. Araujo, and M. Diniz. 2002. Land cover change in two protected areas of Guinea-Bissau (1956-1998). Applied Geography 22(2):139-156.

UNESCO. 2005. Space technology to protect mountain gorillas. Media advisory N°2005-21. United Nations Educational, Scientific and Cultural Organization. http://portal.unesco.org/en/ev.php. (December 2005).

WCPA. *The Durban Action Plan*. 2004. http://www.iucn.org/themes/wcpa/wpc2003/english/outputs/durban/daplan.htm#outcome3. (October 2005).

WDPA Consortium. 2005. World database on protected areas. World Conservation Union (IUCN) and UNEP World Conservation Monitoring Centre (UNEP-WCMC). http://www.unep-wcmc.org/wdpa/

Zhan, X., R. Sohlberg, J.R.G. Townshend, C. DiMiceli, M. Carroll, J.C. Eastman, M. Hansen, and R.S. DeFries. 2002. Detection of land cover changes using MODIS 250m data. Remote Sensing of Environment 83: 336-350.

Chapter 10. Habitat Fragmentation and Connectivity

AUTHORS: Karl Didier[1], Janice Thomson[2]
CONTRIBUTORS: Silvio Frosini De Barros Ferraz[3], Ben White[4]
REVIEWERS: Kurt Riitters[5], Peter Vogt[6], Valerie Kapos[7]

1 Wildlife Conservation Society, 2 The Wilderness Society, 3 University of São Paulo, Brazil, 4 Global Land Cover Facility, University of Maryland, 5 United States Forest Service, 6 Joint Research Centre, 7 UNEP World Conservation Monitoring Centre

Remote sensing based indicators for fragmentation and connectivity:

- Total number of land cover types
- Patch size (largest, average)
- Patch density
- Perimeter-to-area ratio (average)
- Core area index
- Fractal dimension
- Distance to nearest neighbor (average)
- Contagion
- Juxtaposition index
- Road length
- Road density

10.1 Background

Habitat fragmentation is the division of ecosystems or habitats into smaller, less connected patches. It has been defined as the "creation of a complex mosaic of spatial and successional habitats from formerly contiguous habitat" (Lehmkuhl and Ruggiero 1991). Fragmentation results from both natural and human-caused processes.

Connectivity and intactness are closely related concepts (D'Eon et al 2002) to fragmentation: an area that is not fragmented provides continuous habitat, and an area that is fragmented is poorly connected. One can envision a continuum of intactness from a pristine environment on one end to a totally developed environment on the other, with fragmented landscapes occupying the middle of the continuum.

Habitat fragmentation is the result of a number of natural processes, including fire and windthrow (CBD 2005). However, in the context of biodiversity monitoring, fragmentation usually refers to anthropogenic causes such as logging, agricultural development, urban development, and infrastructure development (e.g., roads, utility corridors, oil and gas development, and irrigation canals). Ideally, a baseline condition is established so that an understanding of naturally occurring habitat fragmentation and connectivity from natural processes in a given area or ecosystem type is achieved. Then fragmentation and connectivity indicators are measured to determine human-induced changes that have occurred within the landscape.

There is wide scientific consensus that fragmentation, when coupled with habitat loss, has had overall negative impacts on biodiversity, in terms of both the total number of species in an area and abundance within individual species (e.g., Lovejoy et al. 1986; Laurance et al. 1997; and Nepstad et al. 1999). Many scientists consider the destruction and fragmentation of natural habitats to be a leading cause of the decline and loss of native species (Harris 1984; Wilcox and Murphy 1985; Pickett and White 1985; Wiens et al. 1985; Wilcove 1989; Turner et al. 1993; Noss and Cooperrider 1994; Reice 1994; Newmark 1995; Sinclair et al. 1995; Soule and Terborgh 1999). Negative impacts of fragmentation include decreases in mobility and dispersal of organisms and other natural resources (water, nutrients), increases in mortality resulting from increased exposure to threats (e.g., hunting, fire), and increases in competition from nonnative species.

Roads are a widespread threat to biodiversity loss around the globe through habitat fragmentation. However, roads are also a needed human infrastructure for subsistence activities, trade and economic development, education, medical services, recreation, and other activities of societies. The need for human access should be balanced against the ecological impacts, including reduction in core habitat areas for wildlife; loss of connectivity for wildlife; increase in patch edge effects; diminished animal use of habitats because of noise, dust emissions, and increased presence of humans; interference with wildlife life-history functions (e.g., courtship, nesting, and migration); changes in human behavior such as increased poaching, unethical hunting practices, and recreational activities; physical changes such as the degradation of aquatic habitats through alteration of stream banks and increased sediment loads, spread of exotic species, and mortality from collision with vehicles (Franklin and Forman 1987; Lehmkuhl and Ruggiero 1991; Reed et al. 1996; Forman and Alexander 1998; Trombulak and Frissell 2000). Construction of roads is often the catalyst for a dramatic increase in other anthropogenic threats to biodiversity, such as colonization, land-clearance, and invasion by exotic species.

Similarly, agricultural conversion plays a vital role for society while causing biodiversity loss through removal and fragmentation of natural ecosystem areas and replacement of species assemblages with exotic or domesticated taxa, and through degradation of remaining areas by factors associated with the new land use. For example, modern agricultural techniques can affect biodiversity off-site by (a) diverting water supplies (decreasing the area and/or quality of aquatic and open water habitats); (b) producing high-nutrient agricultural effluent; (c) causing soil erosion; (d) introducing and spreading invasive species, and (e) expanding edge habitats dominated by less threatened species. In addition, agricultural practices may introduce new processes into the disturbance regimes of natural areas (e.g., fire in tropical moist forest ecosystems) that further fragment landscapes.

The effects of fragmentation from roads, agriculture and other development extend well beyond their physical footprint (Franklin and Forman 1987; Chen et al. 1995; Lehmkuhl and Ruggiero 1991; Reed et al. 1996; Lyon and Christensen 2002; Lutz et al. 2003). For example, the openings caused by roads in forested landscapes has been shown to change microclimate conditions (i.e., increased evaporation, temperature, and solar radiation and decreased soil moisture) for some distance into the forest (Chen et al. 1995). Increased competition may occur for species that prefer edges or openings created by roads (Lehmkuhl and Ruggiero 1991). In landscapes fragmented by agriculture, natural habitat edges have been shown to degrade through time because of increased temperature, decreased humidity, increased wind shear, and other factors. As this edge relaxation continues, spaces that were previously occupied by native flora are subsequently colonized by species from adjacent agricultural or secondary ecosystems (Laurance et al. 1997).

Measures of fragmentation and connectivity are most useful as indicators when they can be linked to specific negative impacts on a particular species, habitat type, aquatic system, or other resource (e.g., measures of road density have been linked to reduced habitat effectiveness for elk by Lyon 1983). The response of individual organisms or biodiversity as a whole (e.g., species richness) to most fragmentation indicators requires further research to ensure that the indicators are useful for the system or species of interest. Only a few field studies have documented the negative relationship between connectivity indicators and species diversity (e.g., Goparaju et al. 2005; Jha et al. 2005). Review papers and literature reviews have been published compiling the scientific studies of the effects of roads (including fragmentation effects) on ecosystems and wildlife (Forman and Alexander 1998; Trombulak and Frissell 2000; Gucinski et al. 2001; Gains et al. 2003; Wyoming Game and Fish Department 2004).

As a point of clarity, landscape fragmentation or intactness measures, while valuable as indicators, cannot measure all facets of ecosystem integrity. For instance, the “empty forest syndrome,” in which the canopy structure remains but the wildlife has been hunted out, cannot be effectively monitored through remote sensing and fragmentation metrics.

10.2 Potential Role for Remote Sensing

Remote sensing may be used to map habitat types or land cover across a landscape and to map the impacts of natural and human-caused processes causing fragmentation (e.g., cultivated land or fire scars). The very same imagery and classifications used to determine trends in habitats and ecosystems can be reused for fragmentation or connectivity analyses. In addition to land cover classes, categories of habitat vs. nonhabitat may also be used. Mapped results become the base data for calculating landscape fragmentation metrics and are relatively easy to generate using existing software packages (e.g., FRAGSTATS or Patch Analyst).

Alternatively, the causes of fragmentation (e.g., roads, agriculture, or fire) can be mapped, and then the reciprocal of these areas can be classified as intact patches of habitat. For example, the location of agricultural land use is traceable through time by a wide variety of space-based remote sensing imagery and is currently being quantified annually at local, regional, and national scales for selected parts of the globe (Loveland et al. 1995; Liang et al. 2004; Kerr and Cihlar 2003; Senay and Elliot 2002). At a continental scale, advanced very high resolution radiometer (AVHRR) and MODIS satellite systems can be used to assess both the spatial extent and the health of agricultural systems. Specific types of agricultural systems and different crops can be identified using higher resolution TM, ETM+, and IRS satellites (Oetter et al. 2002). Data from these moderate resolution sensors can also be used in local or site-based analyses for evaluating how an agricultural site is integrated spatially within an agricultural/natural habitat mosaic.

The spatial pattern of roads can be generated from moderate- to high-resolution image data and then used as an overlay to create habitat patches. Weller et al. (2002) generated road data from digital air photos to calculate fragmentation metrics as indicators of wildlife impacts. Moderate-resolution sensors such as TM, SPOT, and IRS are use to delineate road systems and cover larger areas more quickly and cheaply. However, the drawback is that their coarser resolution will cause the omission of some roads that exist on the ground, depending upon road width, canopy type, and spectral contrast. Many of these problems are overcome by using high-resolution photos and digital sensors, typically 1–4 metres in resolution (such as air photos, IKONOS, and QuickBird). Images from these sensors allow direct spatial recognition of the roads in many cases and require less spectral contrast between the road and the surrounding landscape. Drawbacks to these sensors include the high image cost per unit area and the substantially larger volume of data required to cover a project area. In most cases, regional or national projects with high-resolution data sets are not practical at this time because of cost and time required for analysis.

The delineation of roads has typically been done by operator visual interpretation and on-screen digitizing. A human operator can reasonably bring the necessary knowledge and recognition of shape and context in an image; however, techniques are being developed to automate the process of road delineation. It is still associated with a high degree of error and typically still requires a human operator to refine the final road product (Vosselman 1996).

Weller et al. (2002) describes the use of digital air photos (1-metre pixels) to digitize roads in the rangeland in the western United States. (See figure 10.1) The authors digitized roads in an oil and gas field and calculated metrics for the total length of road, road density (the average for the study area and density variation across the landscape), road effect zones, and core habitat areas. Fragmentation metric results were compared with biological literature linking specific road metrics or indicators to the impacts on specific species. For example, the average road density was more than 8 times higher than the road density suggested to adversely affect pronghorn (*Antelocarpa americana*), a prominent big game species that winters in the area.

A similar report by Thomson et al. (2005) measures a number of indicators, including road density, core area, and cumulative distance to road values. The measures are made for the full landscape and for specific land management units, for oil and gas development units, and for wildlife habitat units to allow for the evaluation of current conditions for wildlife and to serve as a baseline for future management options. Comparing indicator results to the wildlife literature, the authors found that 66 percent of elk winter range has road densities greater than what may eliminate effective habitat (figure 10.2). In addition, 100 percent of sage grouse breeding and rearing areas are closer to a road than the avoidance distance recommended during breeding season.

10.3 Connectivity in the Marine Environment

Remotely sensed imagery can also be used to measure some types of connectivity in marine environments. Many species depend on specific habitats (e.g., mangroves, seagrasses, and coral reefs) or networks of these habitats for one or more of their life stages (e.g., Phinney et al. 2001). In addition, the physical condition of channels or inlets can be monitored with imagery. These habitats and the changes in these habitats (depending on size) are often visible using Landsat, ASTER, and MODIS. Many species thrive in productive areas; thus, imagery that provides information about ocean productivity (Ocean Color from SeaWiFS) can let one separate patches of habitat from nonhabitat. Tracking this through time (years), one could potentially see whether areas that are historically productive are still productive or whether these patterns are changing because of pollution or global warming. Connectivity can also be measured in the ocean using altimetry data (e.g., TOPEX) to examine current speed and direction, which can illustrate whether sites are upstream or downstream in terms of larval (and threats) dispersal.

10.4 Ecological and Biodiversity Relevance

Some studies have directly measured the relationship between fragmentation metrics and the response of biodiversity, but generally only for single species or small groups at relatively fine spatial scales (e.g.,

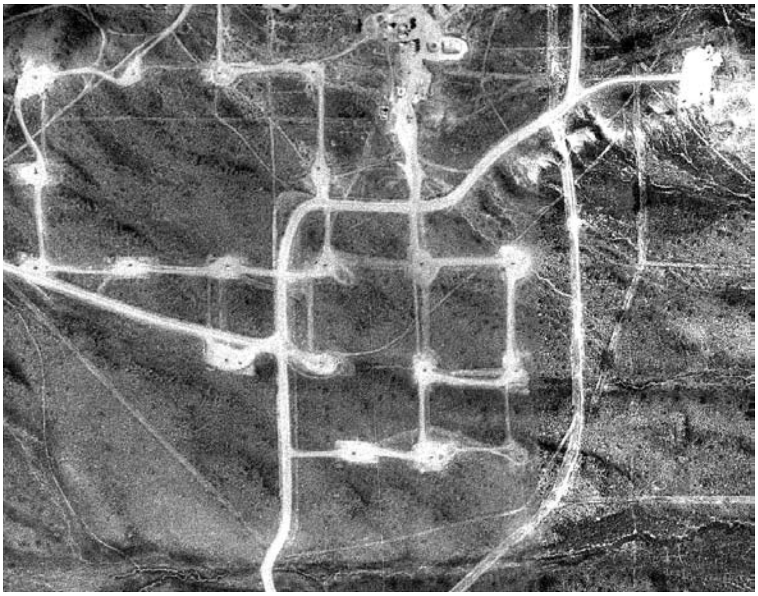


FIGURE 10.1 Roads built for oil and gas development in the sagebrush landscape of the western United States show up clearly in this digital air photo (Weller et al. 2002).

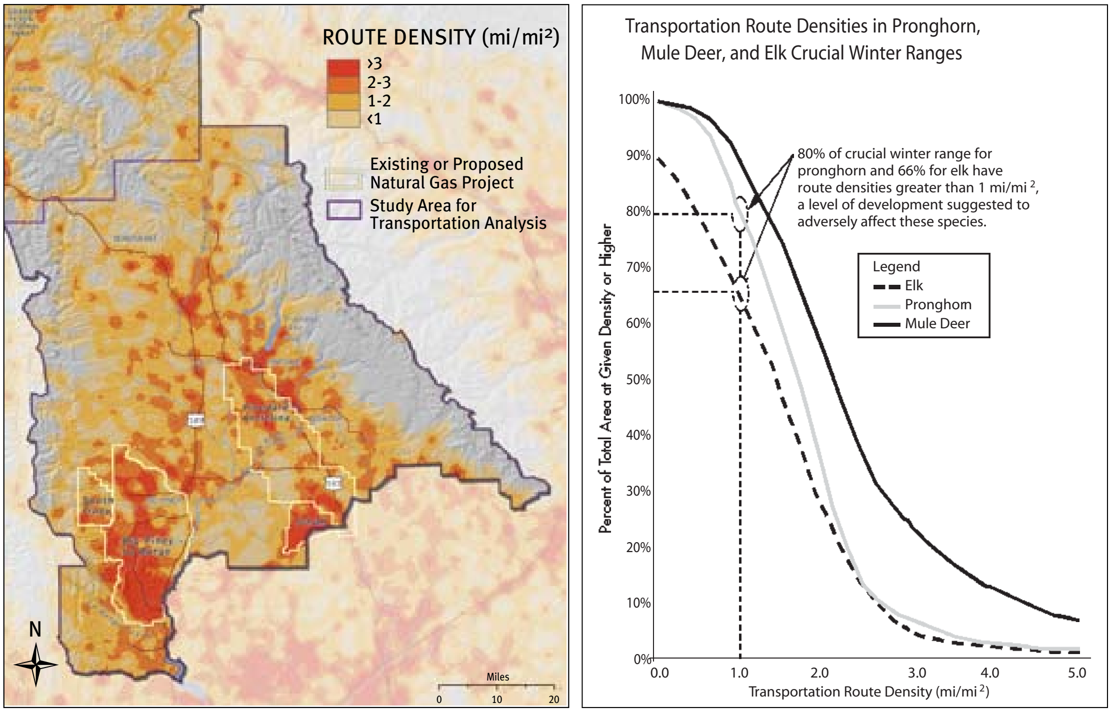


FIGURE 10.2 Road density map of an 11,700 square kilometre oil and gas development management area in the western United States. Accompanying graph shows the cumulative percentage of the landscape within different distances to a road within key wildlife habitats (Thomson et. al. 2005).

Chust et al. 2004; Homan et al. 2004; and Jacuemyn et al. 2002). Few studies have directly linked fragmentation metrics to the response of biodiversity as a whole (abundance or richness), although modelling attempts have been made to generalize the impacts of fragmentation (e.g., Tischendorf 2001; D'Eon et al. 2002).

The causes of fragmentation, as well as biological connectivity requirements (D'Eon et al. 2002) should form the basis for selection of the appropriate fragmentation/connectivity indicators. Whether a landscape is fragmented or connected depends highly on which particular natural functions of the landscape are in peril. An area can be well or poorly connected from the perspective of water flow, soil organisms, nutrients, terrestrial wildlife, dispersing seeds, people, and a myriad of other elements. Any change in fragmentation could have wildly different impacts on these various elements of that landscape. For example, figure 10.5 considers patch connectivity of a landscape (i.e., a configuration metric) from the viewpoint of different organisms. Depending on the particular species, the landscape could be well connected or completed fragmented (Tischendorf and Fahrig 2000; Tischendorf 2001). In addition, if one were considering fragmentation of the landscape for nonliving elements, such as the movement of water, the context would be completely different, and the selection of an indicator that measures habitat connectivity (e.g., nearest neighbor distance) may be irrelevant.

Most fragmentation studies combine the effects of habitat loss on biodiversity with the effects of fragmentation. It is well established that habitat loss has consistently negative effects on biodiversity. Once effects of fragmentation are decoupled from habitat loss, however, fragmentation has been shown to have a weaker effect on biodiversity (although recently Koper et al. (2007) have called this consensus view into question). In many cases it may even have a positive effect (see Fahrig 2003 for more discussion and multiple references.) Therefore, in most cases habitat or ecosystem loss should be considered a superior predictor — and indicator — of biodiversity loss. However, in specific cases where habitat needs of focal species are well understood, fragmentation and/or connectivity should be considered in addition to habitat extent. In other cases, it is useful simply to clarify the relative concentration or diffusion of habitat loss (or lack thereof). Given the ease with which fragmentation information can be produced when input data such as land cover already exists, it can easily be produced as a trial indicator.

10.5 Assessment at National or Continental Scales

It is theoretically possible to develop a national indicator of connectivity that represents the range of biodiversity. Furthermore, index or indicator calculations can be accomplished cheaply and quickly if using data from a pre-existing land cover change series. However, to truly be useful in a management sense, the indicator would have to incorporate measurements across a range of spatial scales, and be interpreted separately for a number of different species with different habitat requirements.

An important consideration is that the accuracy of remotely sensed fragmentation metrics have not been verified using ground truth information, partly because the metrics are derived from land cover data sets. These metrics are susceptible to error since the land-cover data sets on which they are usually based already contain some level of error. Overall accuracy of land cover classifications are are often 80% or lower. However, fragmentation error might exceed that of land cover, because fragmentation is concerned with the edge characteristics of patches and edges, which are where most of the errors in land cover classifications occur (O'Neill et al. 1999). Furthermore, measuring trends requires comparable datasets spanning the desired time period. In most instances, comparable land cover classifications at the scale of desired study are not available. Therefore, most fragmentation studies are snapshots, rather than depictions of trends.

Figure 10.3 represents a national study of change in forest loss and fragmentation over a period of fifty years. Madagascar's forests are among the most biologically rich and unique in the world. Past estimates of forest cover and deforestation have varied widely, so Harper et al. (2007) measured deforestation and forest fragmentation in Madagascar from the 1950s to ~2000 using aerial photography and Landsat imagery. Forest cover decreased by almost 40 percent from the 1950s to ~2000, with a reduction in 'core forest' more than one kilometer from a non-forest edge of almost 80 percent. This forest destruction and degradation threatens thousands of species with extinction. Country-wide coverage of high-resolution, validated forest cover and deforestation data enables the precise monitoring of trends in habitat extent and fragmentation critical for assessment of species' conservation status.

On a continental scale, the work of Riitters et al. (2000) illustrates a study measuring forest fragmentation across continents for a global view of changing forest patterns using AVHRR 1-kilometre land cover data. They developed a method for estimating perforated, edge, and transitional habitats, important indicators in progressively fragmenting forest areas. (Figure 10.4 shows the results for Eurasia.) More recent and improved methods for calculating perforated edge have been produced by Vogt et al. (2007a, b). Riitters et al. (2000) and Wade et al. (2003) describe global forest fragmentation as well. Such analyses have not yet been produced for other biomes (e.g., grasslands, savannas or deserts).

10.6 Fragmentation/Connectivity Metrics

At this time, there is no scientific consensus as to which individual or set of indicators best represents the impacts of fragmentation on *biodiversity as a whole* (Calabrese and Fagan 2004). Hundreds of potential indicators of connectivity, based on the observed structure of the landscape, have been developed, and a number of software packages help users produce and explore the variety of indicators, including FRAGSTATS (McGarigal and Marks 1995, McGarigal et al. 2002), Patch Analyst Extension for ArcView, r.le for GRASS, and Leap II. However, ease of calculation, relationship to the biology of organisms

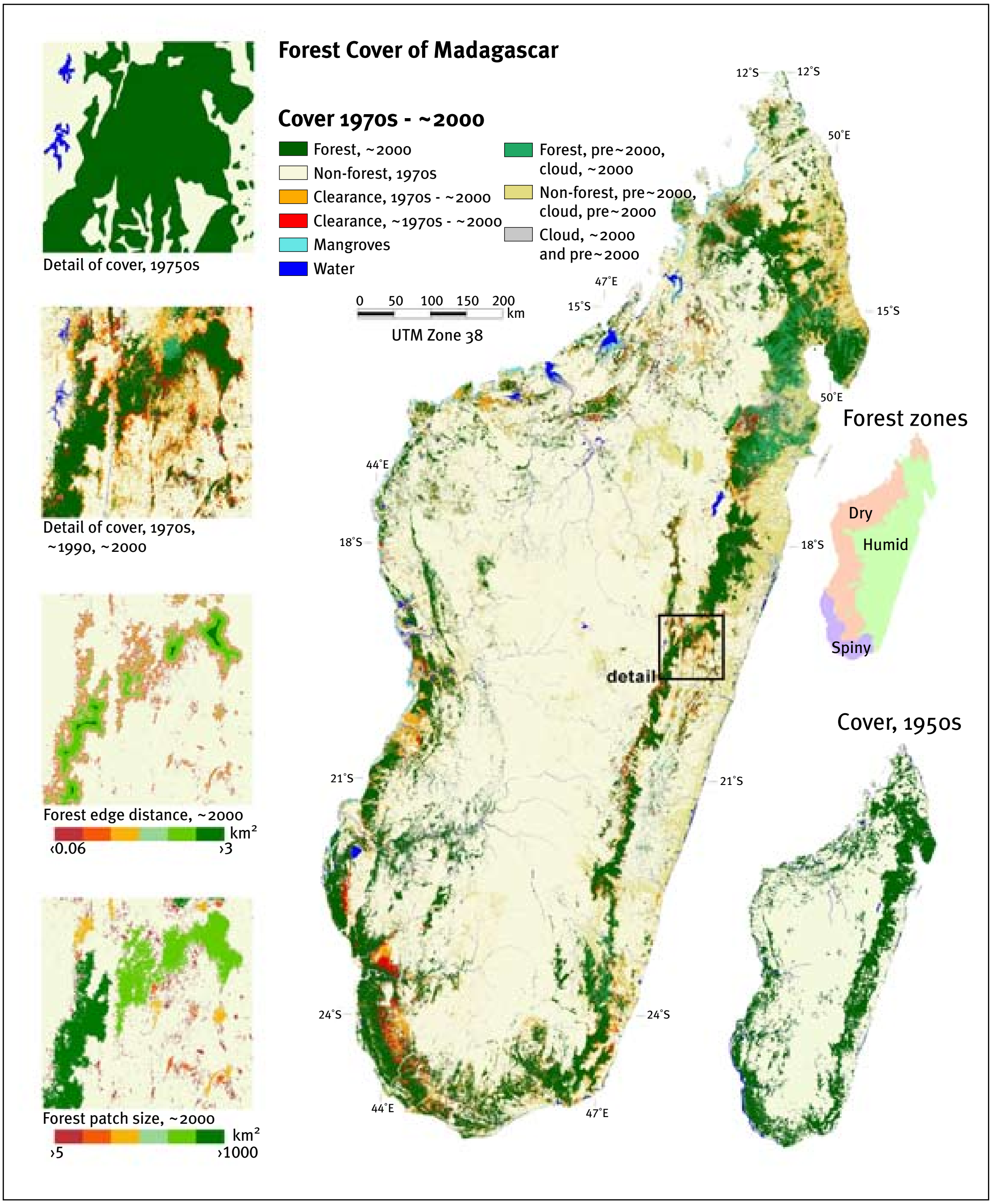


FIGURE 10.3 Forest cover loss and fragmentation in Madagascar from 1950s to ~2000. Forest cover changes from the 1970s to ~2000 are shown in the main figure. Forest cover in the 1950s is shown in the lower-right inset. Details to the left show forest cover as well as forest near edges and in isolated patches. Bioclimatic zones used for reporting cover and rates of change are shown in the upper right inset. Fragmentation is represented as the isolation of forest patches and the creation of edge habitat for an area in east-central Madagascar. Extensive loss and degradation of forest habitat threatens the survival of Madagascar's unique fauna and at the same time jeopardizes human livelihoods. Source: Harper et al. (2007)

TABLE 10.1 Indicators, sensors, and scale of a sample of fragmentation studies.

		Citation	Indicator(s)	Remote sensing product on which indicator was based	Area Covered	Accuracy of remote sensing product
Sensors	AVHRR	Jeanjean and Achard (1997)	Matherton Fragmentation Index	Deforestation-NDVI	1 200 km^2	unknown
		Wade et al. (2003)	Number of pixel edges	Global Land Cover Characteristics	Global	unknown
	MODIS	Giri et al. (2005)	No indicators calculated, but possible	Land cover	Global	unknown
	ETM+/ TM	Jha et al. (2005)	Number of patches, mean patch area, mean patch perimeter	Land cover; NDVI	1 666 km^2	unknown
		Crist et al. (2005)	Number of patches, patch size, patch area, nearest neighbor distance, contagion	Land cover	84 000 km^2	unknown
		Garcia-Gigorro and Saura (2005)	Number of patches, mean patch size, largest patch index, mean radius of gyration, edge length, mean nearest neighbor distance, clumpiness index, patch cohesion, landscape division, aggregation index	Land cover	1 400 km^2	unknown
		Ferraz et al. (2005)	Proportion of land cover types, patch density, largest patch index, mean nearest neighbor distance, juxtaposition/interspersion index	Land cover	900 km^2	82.5% (kappa)
		Riitters et al. (2004)	Interpatch distance, edge amount, mean patch size, patch contrast	Land cover	7.2 million km^2	86% omission/ 94% commission
		Chust et al. (2004)	Angular second moment; landscape heterogeneity index, based on NDVI	Land cover; NDVI	701 km^2	98%
		Colombo et al. (2004)	Geostatistical parameters (range of variogram, sill, nugget distances)	Land cover	13 km^2	unknown

		Citation	Indicator(s)	Remote sensing product on which indicator was based	Area Covered	Accuracy of remote sensing product
Sensors		Millington et al. (2003)	34 FRAGSTAT metrics	Land cover	500-2 500 km^2	unknown
		Fuller (2001)	Number of land cover classes, perimeter-area ratio, square-pixel metric	Land cover	1 350 km^2	84%–93%
	IRS LISS	Jha et al. (2005)	Number of patches, average patch area, average patch perimeter	Land Cover	1 666 km^2	unknown
	IRS LISS	Goparaju et al. (2005)	Patch size	Land cover	2 scenes	90%
	IRS LISS	Amarnath et al. 2003	Patch size and number, perimeter-area ratio, porosity, number of land cover types, Shannon-Weiner index of land cover types	Land cover	1 600km^2	80%–85%
	IRS LISS	Nagendra and Utkarsh (2003)	Patch area, patch shape index, Shannon index for land cover diversity, interspersion-juxtaposition index	NDVI	170 000 km^2	unknown
	IRS WiFS	Garcia-Gigorro and Saura (2005)	See above: ETM+/TM	Land cover	1 400 km^2	unknown
	SPOT	Chust et al. (2004)	Angular second moment; landscape heterogeneity index based on NDVI	Land cover; NDVI	701 km^2	98%
		Jeanjean and Achard (1997)	Matherton Fragmentation Index	Deforestation; NDVI	1 200 km^2	unknown
	ERS	Colombo et al. (2004)	Geostatistical parameters (range of variogram, sill, nugget distances)	Land cover	13 km^2	unknown

(e.g., dispersal capability), and consistency across spatial scales of fragmentation indicators vary greatly (Tischendorf 2001; Rutledge 2002). Fragmentation/connectivity metrics can be measured for individual patches (e.g., patch size) or aggregated across patches at broader scales (e.g., mean patch size within an area). Examples of research using a range of image data and many different types of metrics as indicators are given in Table 10.1. Here, we restrict ourselves to a discussion of metrics meant to characterize broad spatial scales, often referred to as "landscape metrics" (Fahrig 2003). We also bias our discussion to metrics that can be easily measured and compared over two to three time periods in an assessment of trends, as opposed to metrics to compare between large regions or nations.

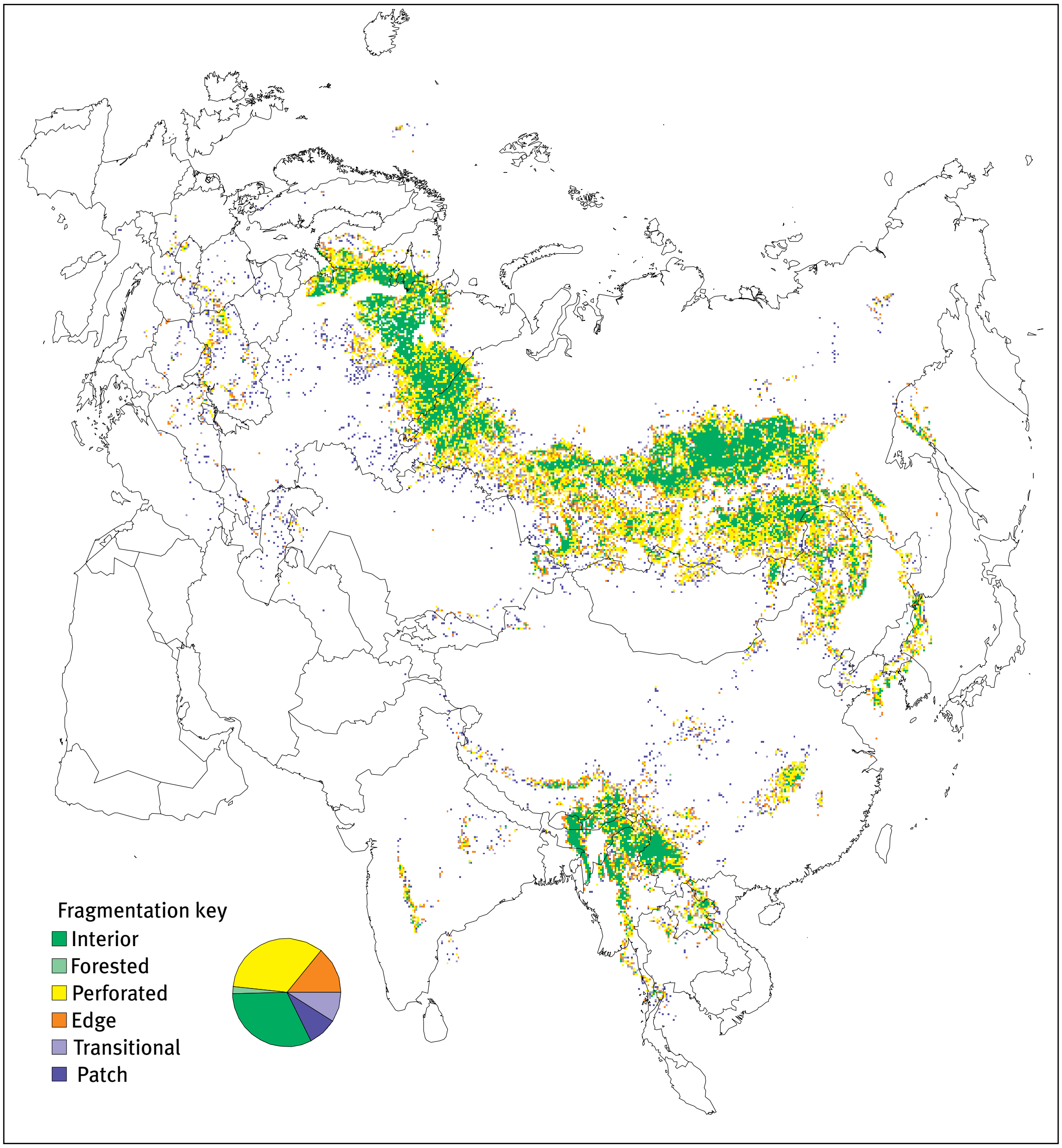


FIGURE 10.4 Forest fragmentation for Eurasia, calculated from land cover data generated from AVHRR image (Riitters et al. 2000). The proportion of each fragmentation category is shown in the pie chart.

There are several review papers of fragmentation metrics that categorize and review the utility of landscape metrics (e.g., Garicia-Gigorro and Saura 2005; Calabrese and Fagan 2004; Moilanen and Nieminen 2002; and Rutledge 2002). Here, we follow a relatively simple and easily interpretable framework for categorizing metrics into five groups, corresponding to different ways that fragmentation is manifest within a landscape: (1) composition, (2) patch size/density, (3) shape, (4) configuration of landscapes, and (5) route networks. However, existing metrics do not always fit neatly into these categories, because often they correspond to two or more characteristics of fragmentation.

Composition metrics are those that describe the types of patch (e.g., forest, agriculture, urban, or habitat versus nonhabitat), including patch-type richness, evenness, and diversity indices (e.g., Shannon's Index). A simple, but consistently useful metric (Cain et al. 1997) suggested by O'Neill et al. (1999) is simply the total number of land cover types (richness). Places or landscapes that are becoming more fragmented over time would see an increase in the number of land cover types.

Patch size/density metrics are sometimes listed as part of composition metrics, but are meant to characterize the size or number of habitat patches within an area. Patch size metrics come in varying forms, from the simple patch density to the more complex effective mesh size (Jaeger 2000). Riitters et al. (2004) used mean patch size. Places or landscapes exhibiting more fragmentation over time would show a decrease in mean patch size.

Shape metrics quantify the complexity of patches, from patches that are more compact (circular) to patches that are more complex in shape. Measures of shape generally are for some perimeter-to-area ratios, but also include more species-specific measurements such as core area index (McGarigal 2002). Fractal dimension is also another common measurement of shape. O'Neill et al. (1999) suggested using two types of shape measurement—average perimeter-area ratio and fractal dimension—for regional assessments, corresponding respectively to different interpretations of patch shape and patch compaction, as described by Riitters et al. (1995). Places or landscapes becoming more fragmented over time would see an increase in the mean perimeter-area ratio and fractal dimension.

Configuration metrics more formally characterize the degree of connectivity or isolation among habitat patches. Metrics based on the distance to nearest neighbor(s) are very common, but range from simple to difficult to calculate based on which patches are considered neighbors. Contagion (raster-based) is a commonly used metric that measures adjacency (the degree of adjacency of pixels across a landscape), and juxtaposition index (McGarigal and Marks 1995) is its vector-based cousin. Unlike contagion, Frohn's (1997) patch-per-unit-area index allows consistent comparison across different analysis extents and resolutions. Riitters et al. (2004) used interpatch distance (average nearest neighbor distance) to measure fragmentation in U.S. forests. O'Neill et al. (1999) suggests calculating a version of contagion for regional-scale assessments.

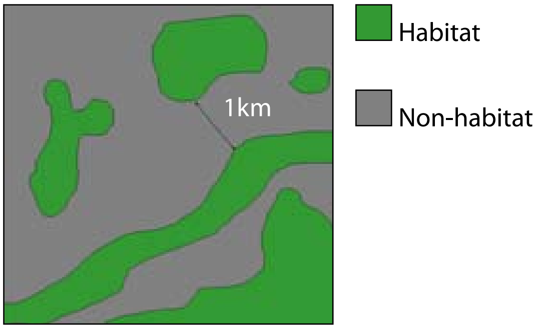
Route network metrics are used to characterize the fragmentation caused by roads, utility corridors, or other linear features that break up otherwise contiguous habitat patches. Road length and road density are among the most common metrics. The area or percent area of habitat within threshold distances of roads (or cumulative distribution for all distances) is also used for specific ecological impacts occurring within known distances of roads. By using the route network data to segment the habitat data, one can use many of the patch metrics described above.

10.7 Key Considerations for Selecting Metrics

No single fragmentation metric (Betts 2000) or even a small set of metrics is perfect for every application. No single metric can represent real-world fragmentation in all its varied forms. To represent the different possible ways that fragmentation manifests itself, a group of at least four to five metrics should be selected to characterize patch composition, size, shape, and configuration across broad areas. As mentioned

a) What is habitat? For a bear, the left map might represent habitat vs. non-habitat, while for a deer, the right map might be better. As a result, the area is poorly connected for a bear, but for a deer, it is well connected.

b) Are distances between habitat patches innately traversable? For a bird, who can travel up to 100km, the area is connected. For a salamander, who can only travel up to 50m, the area is poorly connected.



c) How difficult is it to travel through non-habitat? For a squirrel, it may be safe or easy to travel through non-habitat (left map), but for a tiger, it may be nearly impossible. As a result,

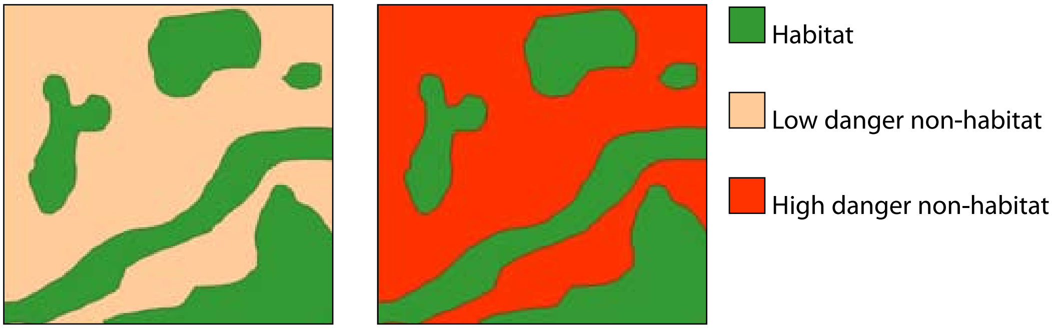


FIGURE 10.5 The challenge of relating connectivity, as measured from landscape structure, to biodiversity impacts.

earlier, specific connectivity needs of local biodiversity should help narrow down the choice of metrics. Further selection of the specific metric should be made with reference to the following considerations.

10.7.1 Sensitivity to scale

Many of the indicators listed above are sensitive to changes in the extent over which they are calculated and, particularly, to the resolution of the input data (e.g., Lawler et al. 2004). If the analysis extent and resolution are kept consistent, different areas or different points in time can be compared relatively easily, using many indicators. Further, O'Neill et al. (1999) suggests that over the range of scales encountered in typical remote sensing data (e.g., 10–100-metre resolution), most of indicators are relatively insensitive to resolution (see Wickham and Riitters 1995 for further discussion).

10.7.2 Calculation complexity and ease of interpretation

The available indicators (e.g., in FRAGSTATS) vary greatly in their calculation complexity and therefore also in the processing time needed to calculate them (and often their ease of interpretation). For instance, for comparing patch size between areas or points in time, mean patch size is likely to be easier to calculate and interpret than mesh size. Consideration of complexity as it relates to processing time will be affected by both the analysis extent and the resolution of the input data. Indicators based on pixel data are likely to require less processing and calculation time than those based on vector data. Indicators are most useful when they can be connected to specific resource needs (e.g., patch size requirements for certain species or road density thresholds for watershed aquatic integrity).

Case Study 10.1: Measuring Tropical Forest Fragmentation in the Amazon (Summary from Ferraz et al. 2005)

Indicators: the proportion of each land-use class, patch density, largest patch index, the mean nearest neighbor distance, and the interspersion/juxtaposition index
Potential monitoring scales: regional and national
Sensor: Landsat TM and ETM+
Imagery cost : Free from various institutions

a. Introduction

The loss of tropical forests in the Amazon has been well documented, yet the landscape patterns and dynamics are not well studied or understood. Central Rondonia in Brazil is among the most heavily deforested areas within the Amazon. Forest is lost from small temporary clearings by small farmers and loggers and larger-scale forest removal for crops and pasture. These activities lead to a complex pattern of forest degradation, including nonforest patches and forest patches at different growth stages.

This study uses satellite data from every other year from 1984 to 2002 to systematically measure changes in forest fragmentation over time to answer some of the following questions: "How did fragmentation occur? What are the landscape trends? When did the matrix transition from forest to pasture? What is the proportion of mature forest that represents a critical threshold? Would the landscape structure be sustainable with the implementation of the 'permanent preservation area' law (Brazil, 1965)?" The analysis of forest fragmentation described here is an integral part of a larger study of landscape dynamics in central Rondonia, including land cover mapping, land-use transitional probabilities, and evaluation of the sustainability of land-use changes in future scenarios.

b. Methods

The study area covers a watershed of approximately 900 square kilometres. Landsat TM and ETM+ images were acquired in even-numbered years from 1984 through 2002. Images were provided by the Land-Use Dynamics Project of the Brazilian Institute for Space Research and by the Tropical Rain Forest Information Center at Michigan State University. For each image date, the images were classified into the three most important cover types in the region: mature forest, secondary forest, and pasture. For each classification, five measures of fragmentation were calculated as indices of landscape structure: the *proportion of landscape* (proportion of each land-use class in the study area—a measure of landscape composition); *patch density* (the number of patches of each land-use class per unit area—a measure of dissection of patches); *largest patch index* (proportion of the landscape occupied by the largest patch of each land use—a measure of patch dominance); the *mean nearest neighbor distance* (the mean distance between patches of the same class—a measure of connectivity); and the *interspersion/juxtaposition index* (indicator of the adjacency of land-use categories—a measure of landscape configuration). Fragmentation measures were generated using FRAGSTATS 3.3 software (McGarigal et al. 2002).

c. Results

The changes in fragmentation measures over time provide indicators of the forest structural dynamics resulting from logging and agriculture. Mature forest has been progressively converted to pasture. Mature forest was lost at an average rate of about 2 percent per year.

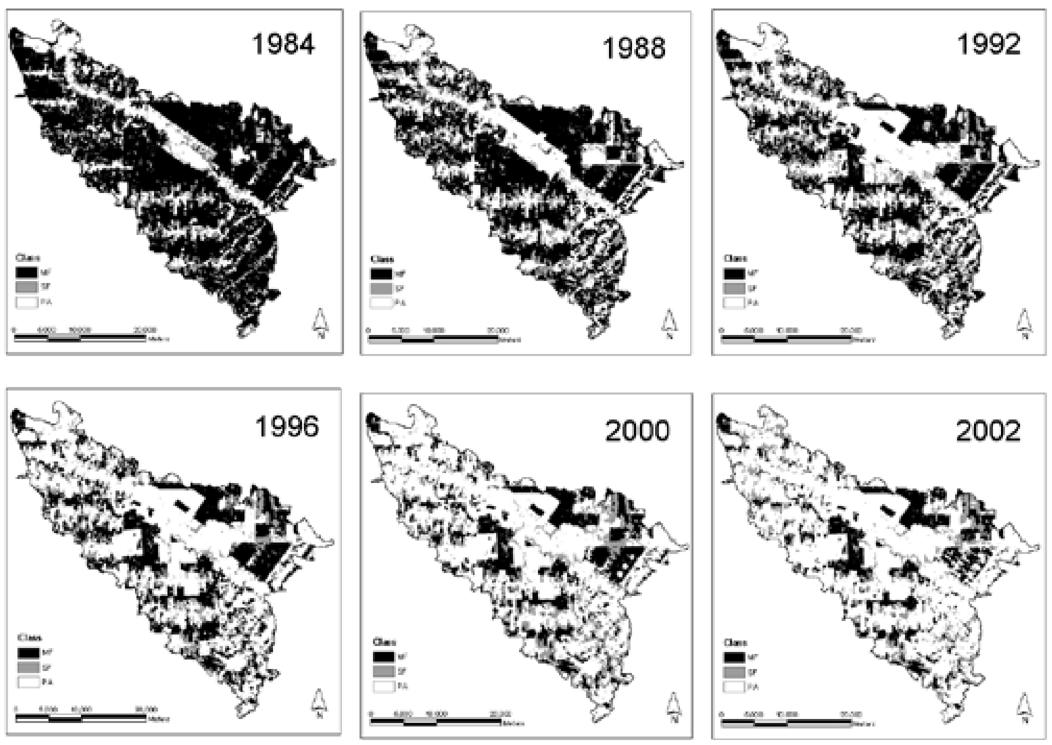


FIGURE 10.6 The loss and fragmentation of forest cover caused by clearing for small farms is illustrated in this time series of forest cover maps (MF = mature forest, SF = secondary forest, PA = pasture).

Looking at the frequency and size distribution of the forest patches showed specific trends in logging practices. Clear-cutting, converting mature forest to pasture, produced mostly small patches (about 1,000 0.5-hectare patches), but far fewer medium and large patches (100 1- to 50-hectare patches; 10 100- to 5,000-hectare patches). Selective logging, converting mature forest to secondary forest, occurs predominantly in small patches (5,000 patches smaller than 0.5 hectare). In fact, most of the total area logged occurs in patches smaller than 5 hectares.

Changing landscape structural dynamics are illustrated by trends in patch density, distance between patches, and the interspersion and juxtaposition index. The patch density for mature forest increased threefold from 1984 to 1996 and then remained relatively stable. The mean distance between patches of forest was little changed until 1996 and then approximately doubled by 2002. Distances between pasture patches followed the inverse pattern and dropped by about one quarter. Notably, 80 percent of deforestation occurs within 3 kilometres of a road, and 80 percent of clear-cutting occurs within 750 metres of existing pastures.

Authors also observed a critical fragmentation threshold of 35 percent mature forest cover. Mature forest loss occurred more rapidly as it declined below this value, suggesting that a minimum of 35 percent mature forest cover should be a target for natural resource managers.

10.8 Data and Other Resources

FRAGSTATS is a publicly available software package that computes a comprehensive variety of fragmentation metrics (McGarigal et al. 2002).

http://www.umass.edu/landeco/research/fragstats/fragstats.html

FRAGSTATS*ARC commercial software integrates some of the most commonly used fragmentation metrics from FRAGSTATS into the widely used ARC/INFO GIS software. It provides a user-friendly interface familiar to many GIS professionals. This is a private product that may be purchased from the developer.

http://www.innovativegis.com/basis/present/fragstat/fragAV%20Info.htm

Patch Analyst is an extension for ArcView GIS software to analyse patches and their attributes. It can be obtained free of charge, but must be used under a license agreement because it is not in the public domain. http://flash.lakeheadu.ca/~rrempel/patch/

r.le programs is a public domain software that runs within GRASS GIS software. It contains a wide range of raster-based fragmentation metrics.

http://72.14.253.104/search?q=cache:xsPMP1dPl0QJ:www.udel.edu/johnmack/frec682/docs/rle21.ps+r.le+Programs+software&hl=en&ct=clnk&cd=3&gl=us

LEAP II uses an older version of FRAGSTATS that is designed to run under the Windows NT environment.

http://www.ai-geostats.org/index.php?id=102

A broader description of all the software listed above can be found at: http://www.umass.edu/landeco/research/fragstats/links/fragstats_links.html

Road-Mapping Tools: An issue of *Photogrammetric Engineering and Remote Sensing* (Vol. 70, No. 12, December 2004) has been devoted to the subject of linear-feature extraction from image data.

10.9 References

Amarnath, G., M.S.R. Murthy, S.J. Britto, G. Rajashekar and C.B.S. Dutt. 2003. Diagnostic analysis of conservation zones using remote sensing and GIS techniques in wet evergreen forests of the Western Ghats – An ecological hotspot, Tamil Nadu, India. Biodiversity and Conservation 12 (12): 2331-2359.

Betts, M. 2000. In search of ecological relevancy: a review of landscape fragmentation metrics and their application for the Fundy Model Forest. Working Group for Fundy Model Forest. New Brunswick Fish and Wildlife Research Units, University of New Brunswick, Canada. http://www.unbf.ca/forestry/centers/fundy/metrics.htm

Cain, D.H., Riitters K., and K. Orvis. 1997. A multi-scale analysis of landscape metrics. Landscape Ecology 12:199-212.

Calabrese, J.M., and W.F. Fagan. 2004. A comparison-shopper's guide to connectivity metrics Frontiers in Ecology and the Environment 2: 529-536.

CBD. 2005. Indicators for Assessing Progress towards the 2010 Target: Connectivity/Fragmentation of Ecosystems. Report from the tenth meeting of the Subsidiary Body on Scientific, Technical, and Technological Advice, Bangkok, Thailand.

Chen, J., J.F. Franklin, and T.A. Spies. 1995. Growing-season microclimatic gradients from clearcut edges into old-growth Douglas-fir forests. Ecological Applications 5(1): 74-86.

Chust, G., J.L. Pretus, D. Ducrot, and D. Ventura. 2004. Scale dependency of insect assemblages in response to landscape pattern. Landscape Ecology 19: 41-57.

Colombo, S., M. Chica-Olmo, F. Abarca, and H. Eva. 2004. Variographic analysis of tropical forest cover from multi-scale remotely sensed imagery. ISPRS Journal of Photogrammetry and Remote Sensing 58: 330-341.

Crist, M.R., B. Wilmer, and G.H. Aplet. 2005. Assessing the value of roadless areas in a conservation strategy: biodiversity and landscape connectivity in the northern Rockies. Journal of Applied Ecology 42: 181-191.

D'Eon, R., S.M. Glenn, I. Parfitt, and M. Fortin. 2002. Landscape connectivity as a function of scale and organism vagility in a real forested landscape. Conservation Ecology 6: 10.

Fahrig, L. 2003. Effects of habitat fragmentation on biodiversity. Annual Review of Ecology, Evolution, and Systematics. Vol. 34: 487-515

Ferraz, S.F.D., C.A. Vettorazzi, D.M. Theobald, and M.V.R. Ballester. 2005. Landscape dynamics of Amazonian deforestation between 1984 and 2002 in central Rondonia, Brazil: assessment and future scenarios. Forest ecology and management, 204: 67-83.

Forman, R.T., and L.E. Alexander. 1998. Roads and their major ecological effects. Annual Review of Ecological Systems 29: 207-231.

Franklin, J.F., and R.T.T. Forman. 1987. Creating landscape patterns by forest cutting: ecological consequences and principles. Landscape Ecology 1: 5-18.

Frohn, R.C. 1997. Remote sensing for landscape ecology: new metric indicators for monitoring, modeling, and assessment of ecosystems. Lewis Publishers, Boca Raton, Florida. 99p.

Fuller, D.O. 2001. Forest fragmentation in Loudoun County, Virginia, USA evaluated with multitemporal Landsat imagery. Landscape Ecology 16: 627-642.

Gaines, W., P. Singleton, and R. Ross. 2003. Assessing the Cumulative Effects of Linear Recreation Routes on Wildlife Habitats on the Okanogan and Wenatchee National Forests. General Technical Report PNW-GTR-586. U.S. Department of Agriculture, U.S. Forest Service, Pacific Northwest Research Station, Portland, OR.

Garcia-Gigorro, S., and S. Saura. 2005. Forest fragmentation estimated from remotely sensed data: is comparison across scales possible? Forest Science 51 (1): 51-63.

GeoCommunity. 2007. Vmap 0, Vector Map Level 0, description and data purchase. Available at: http://store.geocomm.com/data/ (accessed May 2007)

Giri, C., Z.L. Ahu, and B. Reed. 2005. A comparative analysis of Global Land Cover 2000 and MODIS land cover data sets. Remote Sensing of Environment 94: 123-132.

Goparaju, L., A. Tripathi, C.S. Jha. 2005. Forest fragmentation impacts on phytodiversity – An analysis using remote sensing and GIS. Current Science 88: 1264-1274.

Gucinski, H., J.J. Furniss, R.R. Ziemer, and M.H. Brookes. 2001. Forest Roads : A Synthesis of Scientific Information. General Technical Report PNW-GTR-509. U.S. Department of Agriculture, U.S. Forest Service, Pacific Northwest Research Station, Portland, OR.

Harper, G.J., Steininger, M.K., Tucker, C.J., Juhn, D. and F. Hawkins. 2007. Fifty years of deforestation and forest fragmentation in Madagascar. Environmental Conservation, accepted, 2007.

Harris, L.D. 1984. The Fragmented Forest: Island Biogeography Theory and the Preservation of Biotic Diversity. University of Chicago Press, Chicago, IL.

Homan, R.N., B.S. Windmiller, and J.M. Reed. 2004. Critical thresholds associated with habitat loss for two vernal pool-breeding amphibians. Ecological Applications 14: 1547-1553.

Jacquemyn, H., R. Brys, & M. Hermy. 2002. Pathc occupancy, population size and reproductive success of a forest herb (*Primula elatior*) in a fragmented landscape. Oecologia 130: 617-625.

Jaeger, J.A.G. 2000. Landscape division, splitting index, and effective mesh size: new measures of landscape fragmentation. Landscape Ecology 15: 115-130.

Jeanjean, H., and F. Achard. 1997. A new approach for tropical forest area monitoring using multiple spatial resolution satellite imagery. International Journal of Remote Sensing 18: 2455-2461.

Jha, C.S., L. Goparaju, A. Tripathi, B. Gharai, A.S. Raghubanshi, and J.S. Singh. 2005. Forest fragmentation and its impact on species diversity: an analysis using remote sensing and GIS. Biodiversity and Conservation 14: 1681-1698.

Kerr, J.T. and J. Cihlar 2003. Land use and cover with intensity of agriculture for Canada from satellite and census data. Global Ecology and Biogeography 12 (2): 161.

Koper, N., Schmiegelow, F.K.A., Merrill, E.H., 2007. Residuals cannot distinguish between ecological effects of habitat amount and fragmentation: implications for the debate. Landscape Ecology (online first) DOI 10.1007/s10980-007-9083-9.

Laurance, W.F., S.G. Laurance, L.V. Ferreira, J.M. Rankin-de Merona, C. Gascon, and T.E. Lovejoy. 1997. Biomass collapse in Amazonian forest fragments. Science 278: 1117-1118.

Lawler, J. J., O'Connor, R. J., Hunsaker, C. T., Jones, K. B., Loveland, T. R., & White, D. (2004). The effects of habitat resolution on models of avian diversity and distributions: a comparison of two land-cover classifications. Landscape Ecology, 19(5), 515-30.

Lehmkuhl, J. F., and L. F. Ruggiero, 1991. Forest fragmentation in the Pacific Northwest and its potential effects on wildlife. Pages 35-46 in: Ruggiero, L.F., K. B. Aubry, A. B. Carey, and M.H. Huff, tech. coords. Wildlife and Vegetation of Unmanaged Douglas-fir Forests. USDA Forest Service Gen. Tech. Rep. PNW-GTR-285. Portland, OR.

Liang, S., H. Fang, G. Hoogenboom, J. Teasdale and M. Cavigelli 2004. Estimation of crop yield at the regional scale from Modis observations. International Geoscience and Remote Sensing Symposium Proceedings 3: 1625-1628.

Loveland, T.R., Merchant, J.W., Brown, J.F., Ohlen, D.O., Reed, B.C., Olson, P. and J. Hutchinson. 1995. Seasonal land-cover regions of the United States. Ann. Ass. Of American Geographers 85(2):339. doi:10.1111/j.1467-8306.1995.tb0189.x

Lovejoy, T.E., R.O. Bierregarrd, A.B. Rylands, J.R. Malcolm, C.E. Quintela, L.H. Harper, K.S. Brown, A.H. Powell, G.V.N. Powell, H.O.R. Schubart, and M.B. Hays. 1986. Edge and other effects of isolation on Amazon forest fragments. In M.E. Soule, editor. Conservation Biology: the science of scarcity and diversity. Sinauer Associates, Sunderland, Massachusetts, USA.

Luoto, M., Kuussaari, M., & Toivonen, T. (2002). Modelling butterfly distribution based on remote sensing data. Journal of Biogeography, 29, 1027-37.

Lutz, D.W., B.F. Wakeling, L.H. Carpenter, D. Stroud, M. Cox, D. McWhirter, S. Rosenstock, L.C. Bender, and A.F. Reeve. 2003. Impacts and changes to mule deer habitat. Pages 13-61 in: de Vos, J.C. Jr., M.R. Conover, and N.E. Headrick, Eds. Mule Deer Conservation: Issues and Management Strategies. Jack H. Berryman Institute Press, Utah State Universtiy, Logan, UT.

Lyon, L.J. 1983. Road Density Models Describing Habitat Effectiveness for Elk. Journal of Forestry 81 (9): 592-613.

Lyon, L.J. and A.G. Christensen. 2002. Elk and land management. Pages 557-581 in: Toweill, D.E. and J.W. Thomas, Eds. North American Elk Ecology and Management. Smithsonian Institution Press, Washington, D.C.

McGarigal, K. 2002. Landscape pattern metrics. In: A. H. El-Shaarawi and W. W. Piegorsch, (eds.). Encyclopedia of Environmetrics Volume 2. John Wiley & Sons, Sussex, England. pp. 1135-1142.

McGarigal, K., S. A. Cushman, M. C. Neel, and E. Ene. 2002. FRAGSTATS: Spatial Pattern Analysis Program for Categorical Maps. Computer software program produced by the authors at the University of Massachusetts, Amherst. Available at the following web site: www.umass.edu/landeco/research/fragstats/fragstats.html.

McGarigal, K., and B. J. Marks. 1995. FRAGSTATS: spatial pattern analysis program for quantifying landscape structure. USDA For. Serv. Gen. Tech. Rep. PNW-351.

Millington, A.C., X.M. Velez-Liendo, and A.V. Bradley. 2003. Scale dependence in multitemporal mapping of forest fragmentation in Bolivia: implications for explaining temporal trends in landscape ecology and applications to biodiversity conservation. ISPRS Journal of Photogrammetry and Remote Sensing 57: 289-299.

Moilanen, A., and M. Nieminen. 2002. Simple connectivity measures in spatial ecology. Ecology 83: 1131-1145.

Nagendra, H. and G. Utkarsh. 2003. Landscape ecological planning through multi-scale characterization of pattern: studies in the Western Ghats, south India. Environmental Monitoring and Assessment 87: 215-233.

Nepstad, D.C., A. Verissimo, A. Alencar, C. Nobre, E. Lima, P. Lefebvre, P. Schlesinger, C. Potter, P. Moutinho, E. Mendoza, M. Cochrane, and V. Brooks. 1999. Large-scale impoverishment of Amazonian forests by logging and fire. Nature 398: 505-508.

Newmark, W.D. 1995. Extinction of mammal populations in western North American national parks. Conservation Biology 9: 512-526.

NGA (National Geospatial-Intelligence Agency). 2007. NGA Raster Roam, Vector Product Format Download (VMap Level 0). Available at: http://geoengine.nga.mil/muse-cgi-bin/rast_roam.cgi

Noss, R.F., and A.Y. Cooperrider. 1994. Saving Nature's Legacy. Island Press, Washington, DC.

Phinney, J.T., F. Muller-Karger, P. Dustan, and J. Sobel. 2001. Using remote sensing to reassess the mass mortality of Diadema antillarum 1983-1994. Conservation Biology 15: 885-891.

Pickett, S.T.A. and P.S. White (eds.). 1985. The Ecology of Natural Disturbance and Patch Dynamics, Academic Press, 472 pages.

Oetter, D.R., Cohen ,W.B., Berterretche, M., Maiersperger, T.K. and R.E. Kennedy 2001. Land cover mapping in an agricultural setting using multiseasonal Thematic Mapper data. Remote Sensing of the Environment 76: 139-155.

O'Neill, R.V., K.H. Ritters, J.D. Wickham, and K.B. Jones. 1999. Landscape pattern metrics and regional assessment. Ecosystem Health 5(4): 225-233.

Reed, R.A., J. Johnson-Barnard, and W.L. Baker. 1996. Contribution of roads to forest fragmentation in the Rocky Mountains. Conservation Biology 10: 1098-1106.

Reice, S.R. 1994. Nonequilibrium determinants of biological community structure. American Scientist 82: 424-435.

Riitters K.H., , R.V. O'Neill, C.T. Hunsaker, J.D. Wickham. 1995. A factor analysis of landscape pattern and structure metrics, Landscape Ecology, 10 (1):23-39.

Riitters, K. H., Wickham, J. D., O'Neill, R., Jones, B., & Smith, E. (2000). Global-scale patterns of forest fragmentation. Conservation Ecology, 4(2), Art. 3.

Ritters, K.H., J.D. Wickham, and J.W. Coulston. 2004. A preliminary assessment of the Montreal Process indicators of forest fragmentation for the United States. Environmental Monitoring and Assessment 91: 257-276.

Rutledge, D. 2002. Landscape indices as measures of the effects of fragmentation: can pattern reflect process? Manuscript prepared for the New Zealand Department of Conservation. Science and Research Unit, Wellington, New Zealand.

Sanderson, E.W., M. Jaiteh, M.A. Levy, K.H. Redford, A.V. Wannebo, and G. Woolmer. 2002. The human footprint and the last of the wild. Bioscience 52: 891-904.

Schumaker, N.H. 1996. Using landscape indices to predict habitat connectivity. Ecology 77: 1210-1225.

Senay, G.B. and R.L. Elliot. 2002. Capability of AVHRR data in discriminating rangeland cover mixtures. International Journal of Remote Sensing 23(2):299- 312. doi:10.1080/01431160010014855

Sinclair, A.R., E.D.S. Hik, O.J. Schmitz, G.G.E. Scudder, D.H. Turpin, and N.C. Larter. 1995. Biodiversity and the need for habitat renewal. Ecological Applications 5(3): 579-587.

Soule, M.E., and J. Terborgh. 1999. Continental Conservation: Scientific Foundations of Reserve Networks. Island Press, Washington, DC.

Tischendorf, L. 2001. Can landscape indices predict ecological processes consistently? Landscape Ecology 16: 235-254.

Tischendorf, L. and L. Fahrig. 2000. On the usage and measurement of landscape connectivity. Oikos 90: 7-19.

Thomson, J.L., T. Schaub, N.W. Culver, and P. Aengst. 2005. Wildlife at a Crossroads: Energy Development in Western Wyoming. The Wilderness Society, Washington D.C.

Trombulak, S.C., and C.A. Frissell. 2000. Review of ecological effects of roads on terrestrial and aquatic communities. Conservation Biology 14: 18-30.

Turner, M.G., W.H.Romme, R.H. Gardner, R.V. O'Neill, and T.K. Kratz. 1993. A revised concept of landscape equilibrium: Disturbance and stability on scaled landscapes. Landscape Ecology 8: 213-227.

Vosselman, G. 1996. Uncertainty in GIS Supported Road Extraction, ISPRS Congress, Vienna, AIPRS, Vol.31, Part B3.

Vogt, P., Riitters, K.H., Estreguil, C., Kozak, J., Wade, T.G. and J.D. Wickham. 2007a. Mapping spatial patterns with morphological image processing. Landscape Ecology 22:171-177.

Vogt, P., Riitters, K.H., Iwanowski. M., Estreguil, C., Kozak, J., and P. Soille. 2007b. Mapping landscape corridors. Ecological Indicators 7:481-488.

Wade, T. G., Riitters, K. H., Wickham, J. D., & Jones, K. B. (2003). Distribution and Causes of Global Forest Fragmentation. Conservation Ecology, 7(2), art.7.

Weller, C., J. Thomson, P. Morton, and G. Aplet. 2002. Fragmenting Our Lands: The Ecological Footprint from Oil and Gas Development. The Wilderness Society, Washington, D.C.

Wickham, J.D., and K.H. Ritters. 1995. Sensitivity of landscape metrics to pixel size. International Journal of Remote Sensing 16: 3585-3594.

Wiens, J.A., C.S. Crawford, and J.R. Gosz. 1985. Boundary dynamics: A conceptual framework for studying landscape ecosystems. Oikos 45: 421-427.

Wilcove, D.S. (1989) Protecting biodiversity in multiple-use lands: lessons from the U.S. Forest Service. Trends in Ecological Evolution. 4: 385-388.

Wilcox, B.A., and D.D. Murphy. 1985. Conservation strategy: The effects of fragmentation on extinction. American Naturalist 125:879-887.

Wyoming Game and Fish Department (WGFD). 2004. Minimum Recommendations for Development of Oil and Gas Resources Within Crucial and Important Wildlife Habitats on BLM Lands. Wyoming Game and Fish Department, Cheyenne, WY.

Chapter 11. Trends in Invasive Alien Species

AUTHORS: Emma Underwood[1,4], Susan Ustin[2]
CONTRIBUTORS: Aníbal Pauchard[3], Mathieu Maheu-Giroux[3]
REVIEWERS: Maj De Poorter[4], Michael Browne[4]

1 Dept. of Environmental Science and Policy, University of California—Davis, 2 California Space Institute Center of Excellence, University of California—Davis, 3 Universidad de Concepción and Institute of Ecology and Biodiversity, Chile, 4 IUCN Invasive Species Specialist Group

Remote sensing based indicators for Invasive Alien Species

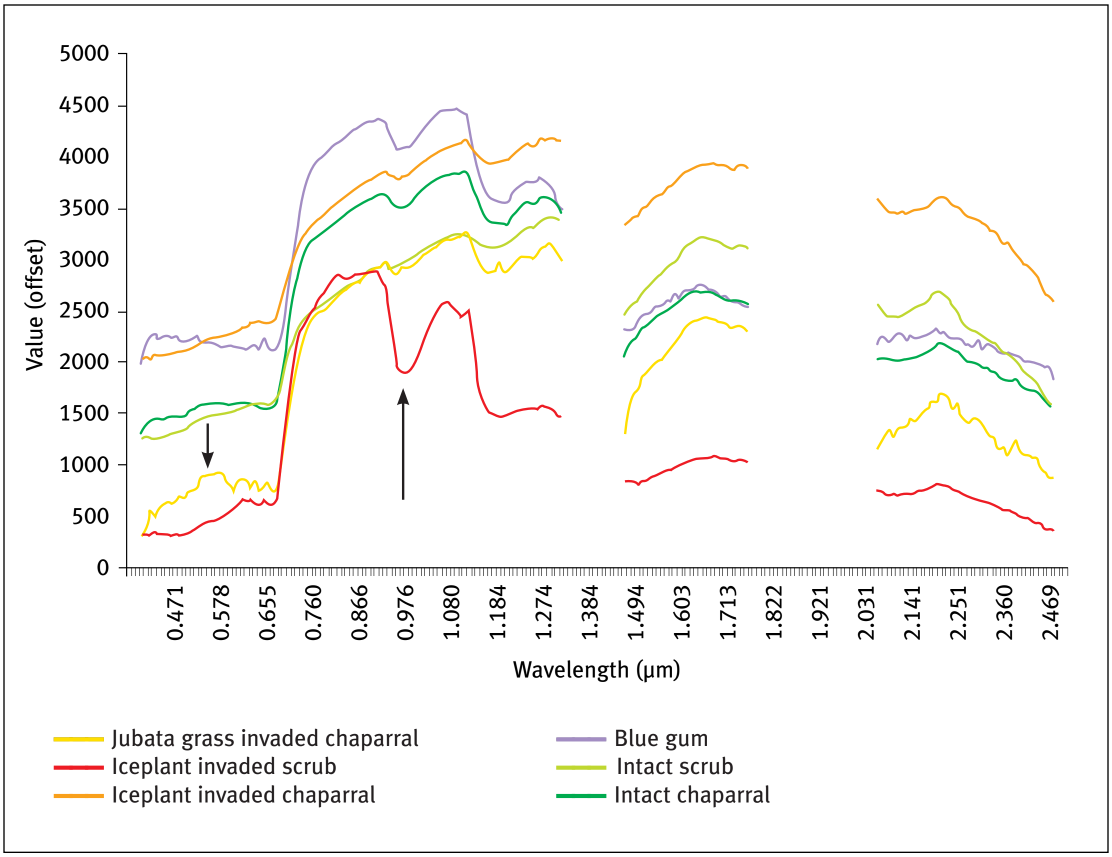
- Area, distribution and trends in particular invasive alien species
- Prediction of the distribution of invasive alien species
- Indirect identification of areas vulnerable to invasion
- Identification of potential sources of invasion and dispersal

11.1 Remote Sensing Technologies for Mapping Invasive Alien Species

Almost every ecosystem on Earth has serious problems with Invasive Alien Species (IAS), with invasions into natural systems representing a key threat to global biodiversity and ecosystem functioning as well as incurring economic costs (Mooney & Cleland 2001; Pimentel et al. 2005). Remote sensing and Geographic Information System (GIS) technologies offer potentially valuable tools for mapping and monitoring IAS as well as providing data inputs for predicting areas susceptible to invasion. Cost effective, large scale, and long term documentation and monitoring of IAS are recognized as fundamental research needs (Johnson 1999) which are increasingly being addressed. Over the last decade the number of publications on remote sensing applications to invasion biology has grown from 20 to 80 publications (Joshi et al. 2004).

The indicators in the beginning of this chapter outline a number of IAS indicators, both direct and indirect, across a range of scales that can be provided by remote sensing. The IAS problem and exchange of species between areas is by its nature global in extent, however, detection and invasion processes occur at more localized scales such as at the site or landscape scale, which is where remote sensing can contribute adequate mapping accuracies to be considered for operational use. Once IAS have become established in a region remote sensing, in comparison to field based techniques, allows an entire region to be mapped simultaneously, image-derived locations of IAS provide a permanent record that can be input into GIS databases for control activities, and repeated acquisitions allow trends in IAS abundance and distribution patterns to be efficiently monitored over time. In contrast, in areas where an IAS does not yet occur, prevention is the most efficient way of dealing with problematic species. Consequently, using remote sensing techniques to map points at risk is valuable, such as mapping airstrips in remote locations or seaports. Alternatively, once an IAS is established in a region mapping potential pathways with imagery can help prevent spread into new areas. For example, roads, hiking and horse trails, and off-road vehicle trails can be mapped—which disperse seeds on vehicle tires or on footwear. Similarly, boat launches can be identified since turbines on boat engines can spread fragments of aquatic invasive plants as well as small invasive aquatic animals such as snails. Since techniques for mapping these features are not specific to identifying IAS we do not review these approaches in this chapter.

Throughout this chapter, for both plants and animals, we use the term "Invasive Alien Species" (IAS). This replaces the various terminologies used in the studies reviewed which includes weeds, non-native, non-indigenous, exotic, alien, or introduced species (Richardson et al. 2000). We also focus primarily



B. Iceplant (Carpobrotus edulis)

C. Jubata grass (Cortaderia jubata)

© J.M. Randall/The Nature Conservancy[2]

FIGURE 11.1 A Comparison of spectral reflectance from different vegetation types two of which are dominated by invasive alien species. Values on y-axis are offset for clarity. The IAS include: B. Iceplant (Carpobrotus edulis), noted for its thick, succulent leaves causing a deep water absorption feature (see up arrow at 0.9 µm) and C. Jubata grass (Cortaderia jubata), characterized by dry foliage and a lighter green reflectance (see down arrow at 0.55 µm)[1].

1 Reprinted from the Journal of Environmental Management, Volume 39, Underwood, E. C., S. L. Ustin, and C. M. Ramirez, 'A comparison of spatial and spectral image resolution for mapping invasive plants in coastal California', Pages 63-83, Elsevier Inc, Copyright (2007), with permission from Elsevier.

2 Reprinted from Remote Sensing of Environment, Volume 86, Underwood, E. C., S. L. Ustin, and D. DiPietro, 'Mapping nonnative plants using hyperspectral imagery', Pages 150-161, Elsevier Inc, Copyright (2003), with permission from Elsevier.

on detection of invasive plants or native plants impacted with by an invasive species (e.g., pathogen), as these have received more attention using remote sensing applications than mapping invasive animals.

11.2 How Does Remote Sensing Distinguish Invasive Alien Species?

The characteristics of a particular invasive plant species, both of the individual and also in relation to its surroundings, determine whether remote sensing techniques are appropriate. Many plant species, however, are not appropriate for image-based detection because they are indistinguishable from surrounding species or are understory species whose direct detection from remote sensing is almost impossible. In these cases indirect methods of mapping including the use of GIS data layers and modelling can be used (Joshi et al. 2004). For IAS present in the vegetation canopy successful detection approaches have generally capitalised on unique phenological or biochemical properties, structural characteristics, or the spatial patterns of infestations.

11.2.1 Biochemical characteristics

Remote sensing images record the reflectance spectra of vegetation (and other land-cover elements such as soils and geologic minerals) within each pixel (picture element) based on their interactions with electromagnetic radiation in the solar region. Spectral characteristics of plants are derived from biochemical absorption features related to chlorophyll and other pigments, water, proteins, starches, waxes, and structural carbohydrate molecules such as lignin and cellulose (Elvidge 1990; Fuentes et al. 2001; Penuelas et al. 1997). Identification generally targets differences in the abundance and timing of these characteristics among species. For example, the strong water-absorption features associated with the succulent leaves of pickleweed (*Salicornia virginica*) (Sanderson et al. 1998) or iceplant (*Carpobrotus edulis*) (See figure 11.1) influence spectral properties which are detectable by remote sensors.

11.2.2 Phenological characteristics

Detection by remote sensing can be facilitated by the timing of image acquisition to correspond with particular periods during the life cycle of a target IAS, or the acquisition of two images at different times in the life cycle. Some IAS become greener more quickly than surrounding species in the spring or alternatively senesce earlier, e.g., cheatgrass (*Bromus tectorum*) or yellow starthistle (*Centaurea solstitialis*) (Miao et al. 2006). Alternatively, the flower colour of the target invader may be distinct compared to surrounding species, such as the yellow bracts of leafy spurge (*Euphorbia esula*).

11.2.3 Structural characteristics

Where the canopy cover of the plant infestation is either dense or uniform the spatial patterning of the target species is often detectable. For example, the rhizomatous spread of iceplant (*Carpobrotus edulis*) produces a dense, uniform cover that assists in detection (See figure 11.1). Alternatively, detection can be assisted by the canopy architecture—branching patterns and leaf attachments—of IAS compared to the surrounding vegetation. For example, structural differences between common reed (*Phragmites australis*) and the surrounding grass and tree vegetation types allowed for successful mapping of this invasive (See figure 11.2). Alternatively, the use of high spatial resolution lidar imagery which can detect small changes in the height of vegetation has been used in conjunction with aerial photography for mapping IAS in salt marshes and wetlands, e.g., *Spartina spp.* (Rosso et al. 2005).

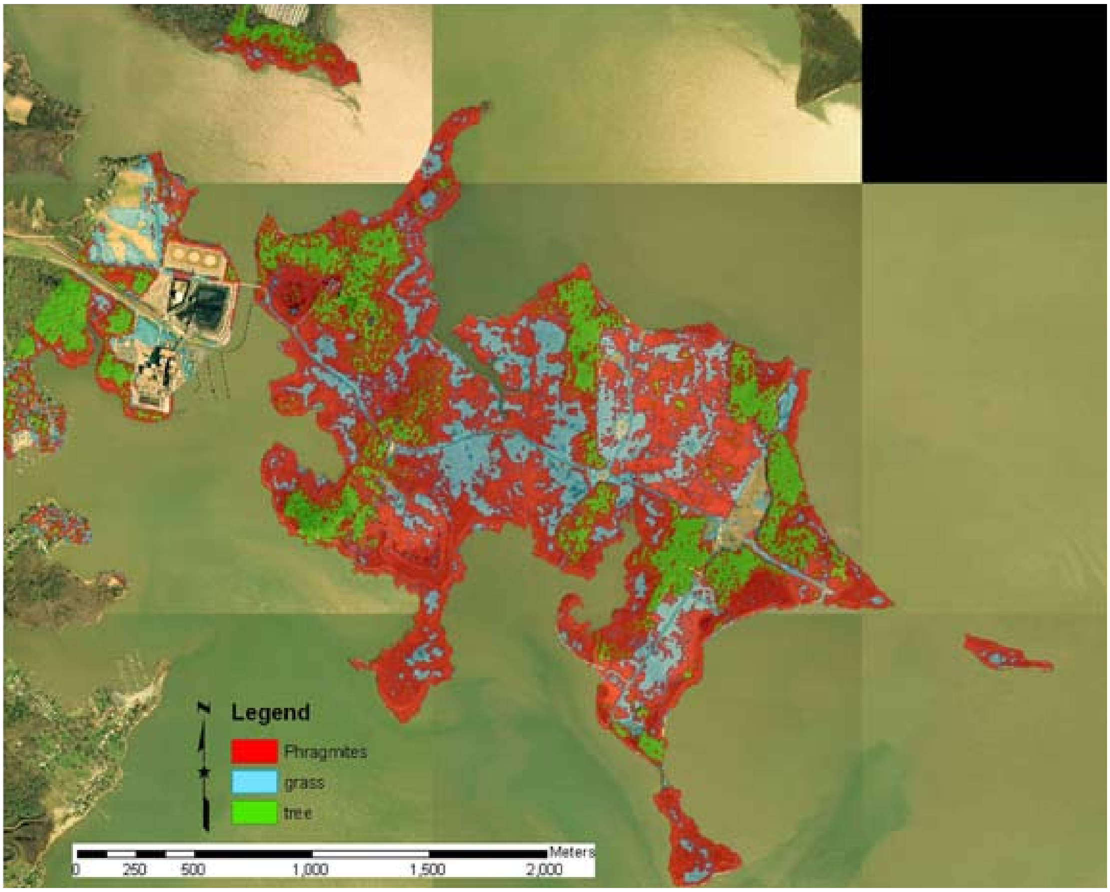


FIGURE 11.2 Classification of common reed (Phragmites australis), trees and grasses on Carroll Island in the Chesapeake Bay, USA using hyperspectral AVIRIS imagery. (Source: John Kefauver, unpublished data, CSTARS).

11.3 Types of Imagery for Identifying Invasive Alien Species

The application of remote sensing to invasive alien plants has seen a transition from the use of imagery with a high spatial but low spectral resolution (such as black and white or colour infrared aerial photographs) to digital images with greater spectral resolution although coarser spatial resolution, and more recently to imagery that couples both high spatial and high spectral resolution.

11.3.1 Aerial photography and videography

At one end of the continuum of resolution options, aerial photographs have the benefit of being relatively inexpensive and typically have very fine spatial resolution (0.1–2 m). This spatial resolution meets most criteria for sampling invasive plant species of current management interest even in the smallest patch sizes, albeit not for many understory species or grasses in mixed grasslands which may not form distinct patches. Aerial photography (digital or film) and digital videography are particularly appropriate where an IAS has unique visual characteristics that readily distinguish it from the surrounding vegetation (see case study 11.1 and figure 11.3). Chinese tamarisk (*Tamarix chinensis*) has been identified with aerial photography using its unique orange-brown colour prior to leaf drop (Everitt et al. 1996). High resolu-

FIGURE 11.3 Aerial photograph of a creek segment in the Central Valley of California, USA. The red arrows indicate two large tamarisk (Tamarix spp.) shrubs in flower, giving the canopy a distinctive pink hue. In a complex environment like this, the accuracy of the IAS map depends on the skill and experience of the photo-interpreter. (Photo: Deanne DiPietro, CSTARS).

tion infrared aerial photography was used to map a number of woody invasives, including blackberry (*Rubus fruticosus*), European olive (*Olea europaea*), and *Pinus species* in the Mount Lofty Ranges of South Australia (Crossman & Kochergen 2002). Visual and computer assisted interpretation of digital infrared images were also used to successfully map invading *Acacia* species from surrounding native vegetation and other IAS in the fynbos biome of South Africa (Stow et al. 2000). In the aquatic realm, expert interpretation of colour aerial photographs was successful in mapping submerged aquatic vegetation in the Chesapeake Bay, Maryland, USA (Orth & Moore 1983).

While aerial photography is relatively inexpensive and can be acquired at high spatial resolution, disadvantages include extensive manual labor for processing and time-intensive interpretation requiring both skill and experience (Anderson et al. 1993; Everitt et al. 1995). Also, to capture spectral differences in the target species compared to surrounding vegetation image acquisition needs to be carefully coordinated with the timing of field measurements. Given these limitations data collection is feasible only over relatively small geographic areas.

Case study 11.1: Acacia dealbata invasion across multiple scales: Conspicuous flowering species can help us study invasion pattern and processes

Authors: Aníbal Pauchard and Mathieu Maheu-Giroux

Multiscale approaches are powerful tools to understand the processes, patterns and impacts of biological invasions (Pauchard & Shea 2006). While some IAS can be difficult to detect with remote sensing techniques, other species are particularly detectable due to their distinct spectral signature and unique phenology. *Acacia dealbata* (silver wattle) is an invasive species in south-central Chile native to Australia, which flowers in the middle of winter, providing a clear and intense yellow pattern that can be distinguished using colour aerial photography (see figure 11.4).

FIGURE 11.4 Acacia dealbata (silver wattle)

Acacia dealbata is associated with human disturbance, particularly road construction, and invades many areas in the coastal range of south-central Chile as well as riparian corridors. Competitive effects with native forests are still unknown, as it is currently associated with disturbed environments such as exotic tree plantations (e.g., *Pinus* or *Eucalyptus*). To determine the impact of *A. dealbata* across multiple scales, we first assess the current extent of invasion across the landscape by taking advantage of the species' winter yellow flower, which is unique compared to any other species in the region (native or exotic). We randomly selected three landscape quadrants (9 km x 9 km). In each quadrant, we georectified 1:20,000 digital colour photographs acquired in the winter using ortho-rectified images (1:115,000) and a minimum of 25 ground control points (using ArcGIS 9 software). The positional accuracy of the georectification was assessed using more than 30 reference points and the Root Mean Square Error was 8.45-13.65 m (Green & Hartley 2000). To maintain positional accuracy in our datasets, the minimum mapping unit needed to be at least twice the maximum RMSE (Ford & C.I. 1985; Walsh et al. 1987); consequently, a pixel size of 30 metres was chosen to record the presence/absence of

A. dealbata. A vector grid consisting of 30 m x 30 m cells was created and overlaid on each landscape quadrat. In each pixel, using visual photo-interpretation, presence of *A. dealbata* was recorded when more than 5% of the pixel was occupied by the species (See figure 11.5).

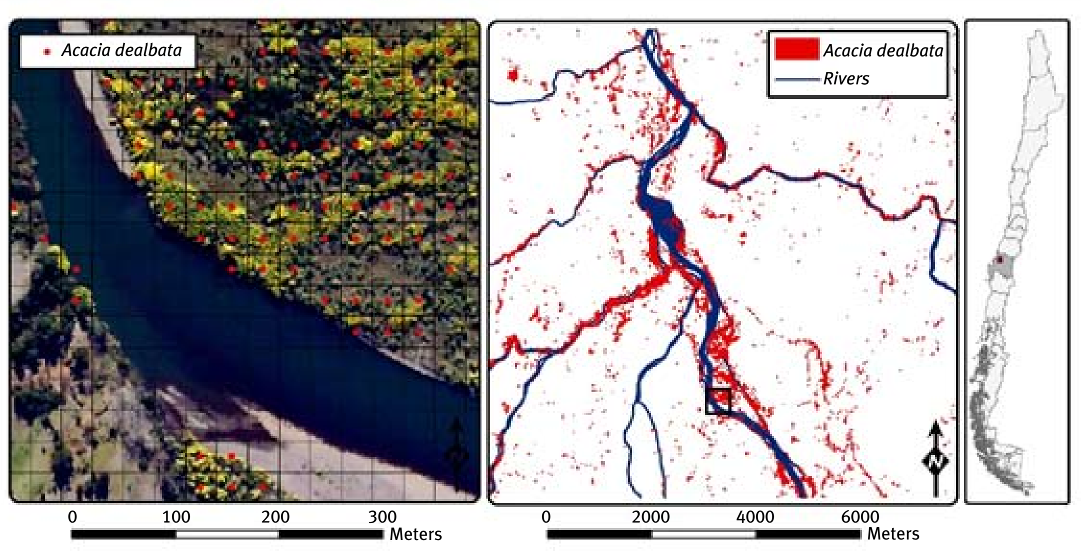


FIGURE 11.5. Grid cells identified with Acacia dealbata present using colour aerial photographs, final classification across study area, and location map of the study area in Chile.

To increase our understanding of the invasion of *A. dealbata,* we analysed the relationship between the mapped infestations with a number of data layers (e.g., roads, rivers, land use). Preliminary results derived using logistic regression techniques show the species is significantly associated with rivers but less so with roads ($p<0.01$). There is significant aggregation of the species from the stand to the landscape scale (Modified Ripley's K, *L*-function transformation (Besag 1977)), which illustrates that the species has a continuous distribution over the landscape once it establishes itself in a new location. This pattern may also indicate that the species is still spreading over the landscape and that limitations for establishment may be more related to propagule pressure than to environmental conditions.

Our current research focuses on relating species invasions to multiple environmental variables at different spatial scales and identifying how those relationships change as the scale of observation changes. For that purpose, we are considering a range of pixel size from 5 m to 150 m and also adjusting the size of the quadrants. For example, using the same aerial photographs, processes such as dispersal of the invasion front and percolation of the species into native ecosystems could be identified using 5 m pixels and quadrants of 1 km x 1 km.

Our methodological approach is relatively easy to conduct and replicate and requires neither highly skilled personnel nor expensive software nor hardware. However, due to the human-based decision process, biased and random errors can influence the presence/absence pixel classification. This can be especially problematic if the photographs are not acquired at peak flowering. This study indicates there is a tremendous potential for monitoring the spread of invasions of *A. dealbata* in Chile using a relatively low-cost option of digital aerial photography, which can be readily applied to other IAS with distinct spectral characteristics. In turn, patterns identified using conspicuous flowering species can serve as models to increase our understanding of IAS, particularly of those that are difficult to detect using remote sensing techniques at broader spatial scales.

11.3.2 Multispectral imagery

In contrast to aerial photography and videography, the use of digital multispectral imagery offers coverage over larger spatial areas, objective change detection through direct analysis of historical image archives, and the opportunity for automated image processing. Even coarse scale AVHRR imagery has been used to distinguish moderate to heavy infestations of broom snakeweed (*Gutierrezia sarothrae*) from surrounding grassland species by capitalising on differences in phenological activity (Peters et al. 1992). Measurements of water clarity and turbidity from AVHRR images collected in different seasons were found to be accurate indicators of the locations of zebra mussels (*Dreissena polymorpha*) in Lake Huron, USA (Budd et al. 2001). Clearly, these examples represent IAS that have spatially extensive distributions and background conditions that remain relatively consistent over large areas. At a medium spatial and spectral resolution, Landsat TM imagery has been used successfully to map target weed species that are spectrally or temporally unique. SPOT imagery has been used to successfully identify speargrass (*Imperata cylindrica*) invading savanna areas in Cameroon (Thenkabail 1999). SPOT has also been suggested to be an appropriate sensor for monitoring the control of emergent aquatic invasive plants such as water hyacinth (*Eichhornia crassipies*) in Bangalore, India using NDVI (Venugopal 1998). In one study, Landsat ETM+ imagery has been used to indirectly map IAS in the understory based on forest canopy density and light intensity reaching the understory in lowland forests in Nepal (Joshi et al. 2006).

Multiband imagery offers some clear advantages over aerial photographs and videography but the coarse spatial and spectral resolution of AVHRR, MODIS, and Landsat (E)TM present challenges when infestations are neither continuously widespread, dense, nor monospecific. This might include some common and economically important invasive plants that mix with other species or have thin canopies that pass light from underlying vegetation and soil which can be surprisingly difficult to distinguish.

11.3.3 Hyperspectral imagery

New technologies such as hyperspectral imagery (also known as imaging spectroscopy) hold great promise for mapping IAS. This technology, characterized by many narrow spectral bands, allows detailed spectra to be acquired for each pixel in an image (see figure 11.6). Subtle differences in reflection and absorption patterns can be detected resulting in the identification of individual species, higher mapping accuracies, and even the potential for mapping IAS that grow at low densities.

As with other types of imagery, discrimination of the target species based on the distinctive colour of the target plant has been successfully used for mapping. For example, the white flowers of perennial pepperweed (*Lepidium latifolium*) allowed this species to be discriminated in the Sacramento-San Joaquin Delta region of central California, USA (Andrew & Ustin 2006). In freshwater systems, again in the Delta, the greenness of water hyacinth (*Eichhornia crassipes*) compared to surrounding vegetation permitted successful mapping of this emergent invasive (Mulitsch & Ustin 2003). In contrast to other image types, the increased spectral resolution of hyperspectral imagery is able to capitalise on specific biochemical and structural properties of target invaders, e.g., cellulose and lignin features caused by the dry foliage and stems of jubata grass (*Cortaderia jubata*) (see figure 11.1C) and the nitrogen and water content of the fire tree (*Myrica faya*) in Hawaii (Asner & Vitousek 2005; Underwood et al. 2007)

Hyperspectral imagery offers a number of advantages over coarser resolution sensors, although mapping IAS is still largely restricted to those which dominate the vegetation canopy. Disadvantages include the small number of airborne image providers, its expense, the large file sizes associated with the imagery and the expertise often required for processing.

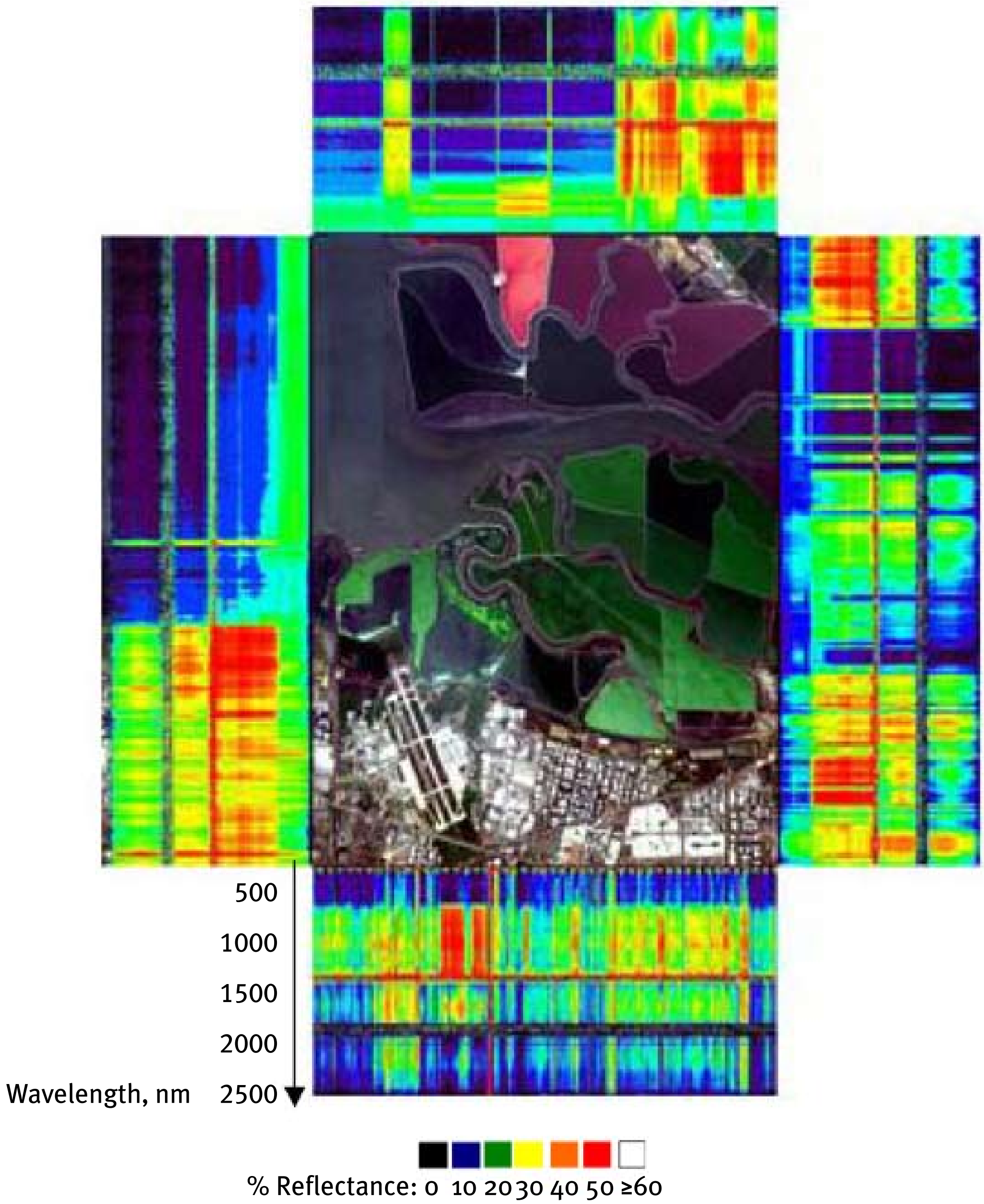


FIGURE 11.6 Hyperspectral data from NASA's AVIRIS sensor. The centre of this figure is a pseudo-true colour image of the salt pans and urban area of the San Francisco Bay, California, USA. The image surface is surrounded by a colour coded display of the variability in reflectance of the edge pixels for each of the 224 spectral bands. Data are oriented so that the bands closest to the image are at the shortest wavelength, here 400 nm, and the bands furthest from the image are at the longest wavelength, 2500 nm. The reflectance in each band is colour coded: 0-5% is black, 5-15% is blue, 15-25% is green, 25-35% is yellow, 35-45% is orange, 45-55% is red and 55% and higher reflectance is white.

11.4 Tradeoffs Between Image Resolution and Mapping Accuracy

The selection of image resolution has clear implications for the accuracy of mapping target IAS or infested vegetation communities. However, while systematic comparisons of different types of imagery over the same spatial area would be valuable for comparison, there are few valid examples for IAS, and consequently limited guidelines to help inform the selection of appropriate image types. A study mapping invasive plants in riparian areas in South Africa found vegetation identification was most accurately derived with 1:10,000 black and white aerial photographs using manual techniques, while coarser spatial resolution aerial videography and Landsat TM imagery yielded lower accuracy (Rowlinson et al. 1999). Low mapping accuracies with the Landsat image were attributed to the large pixel size relative to the scale of riparian vegetation distribution. In Montreal, Canada, the accuracy of similar resolution panchromatic and colour aerial photographs were compared to map a common reed (*Phragmites*

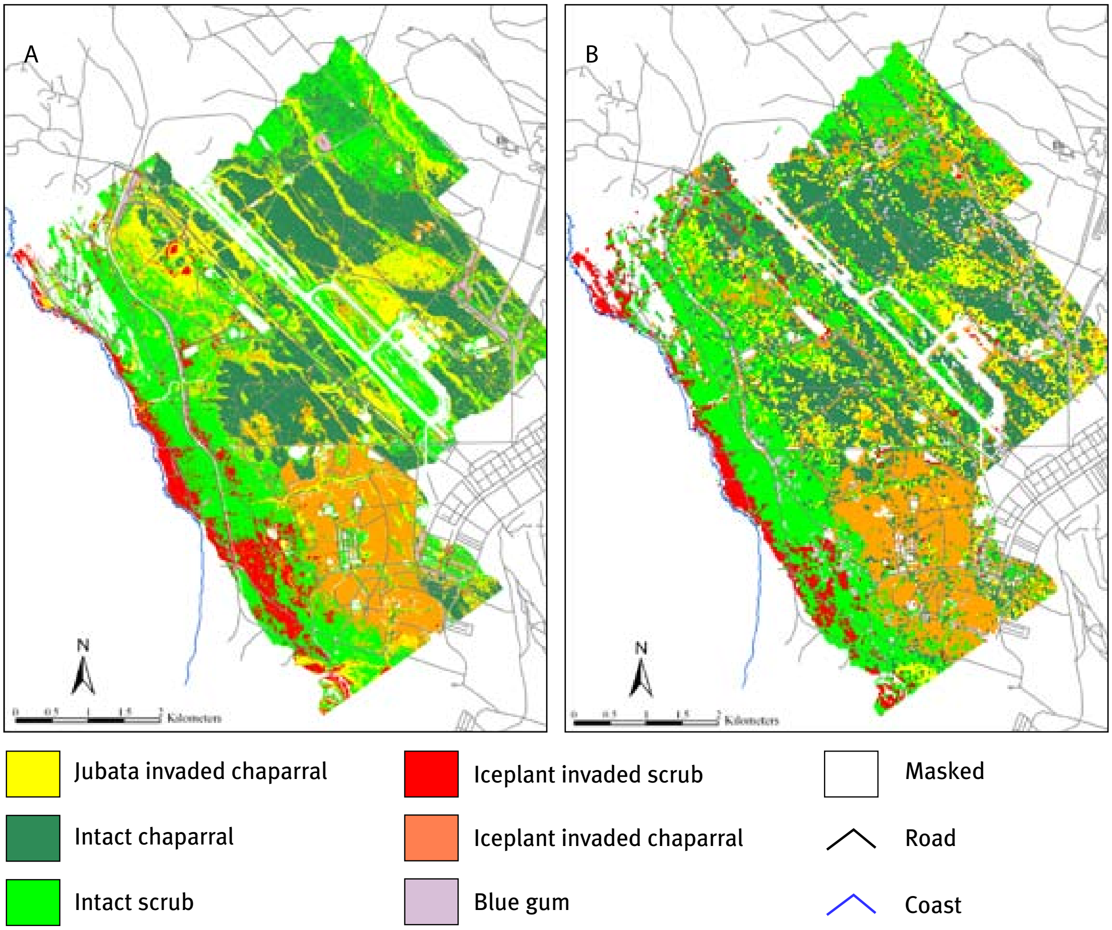


FIGURE 11.7 Classification of six vegetation types at Vandenberg Air Force Base, California, USA: A. Hyperspectral (AVIRIS) image (4 m and 174 wavebands) and B. Landsat ETM (30 m and 6 wavebands)[3].

3 Reprinted from the Journal of Environmental Management, Volume 39, Underwood, E. C., S. L. Ustin, and C. M. Ramirez, 'A comparison of spatial and spectral image resolution for mapping invasive plants in coastal California', Pages 63-83, Elsevier Inc, Copyright (2007), with permission from Elsevier.

australis) along roadsides and agricultural ditches (Maheu-Giroux & de Blois 2005). Findings indicated colour images with greater spectral resolution produced higher accuracy results. A study in the central coast of California, USA compared the accuracy of mapping six vegetation types—three of which were dominated by three IAS: iceplant (*Carpobrotus edulis*), jubata grass (*Cortaderia jubata*), and blue gum trees (*Eucalyptus globulus*) (Underwood et al. 2007). Overall mapping accuracies ranged from 75% using hyperspectral (AVIRIS) imagery (4 m and 174 wavebands) to 50% using Landsat ETM imagery (30 m and 6 wavebands) (See figure 11.7). By comparing imagery with different combinations of spatial and spectral resolutions, findings suggest for IAS with distinct characteristics outside the visible spectrum that mapping accuracies are highest when imagery has greater spectral than spatial resolution.

Deciding on the appropriate image resolution is further confounded by the well recognized tradeoff between spectral and spatial resolution and the cost and ease of processing the data. Hunt et al. (2005) compared different types of imagery for a study area of 100 km^2 and found Landsat TM to be cheapest at less than \$500, followed by digital videography or moderate resolution imagery (e.g., SPOT) at less than \$1,000, with hyperspectral imagery the most expensive at around \$10,000 for the same size of study area. Again, as with mapping accuracy, there have been few standardized comparisons of the costs of remote sensing techniques over the same study area.

11.5 Identifying the Potential Distribution of Invasive Alien Species

Although not a substitute for regular systematic field surveys, distribution models can provide a valuable tool to predict locations where undetected populations of particular species are most likely to occur. This can assist in prioritising limited resources such as personnel, time, and funding for control and monitoring purposes. Many predictive models consist of statistical "niche modelling", where presences (e.g., from locations where herbarium specimens were collected) or presence-absence (e.g., from vegetation plots) data are used to infer an "environmental envelope" that contains most of the presence locations. Remotely sensed data such as vegetation, climate, soils, geomorphology, adjacency to roads or footpaths, and information on management techniques (e.g., grazing intensity maps) can be used as predictors in these models. Alternatively, mechanistic models are more likely to take advantage of species tolerances (e.g., soil, moisture, elevation, and temperature extremes) established by experimental studies and use remotely sensed data to identify locations with high suitability with respect to multiple stressors or limiting resources. As illustrated in the studies reviewed in the following paragraphs, predictive modelling approaches have been applied at the global, national, landscape and site spatial scales (Morisette et al. 2006; Schnase 2003; Thuiller et al. 2005).

At the national scale, a habitat suitability map for salt cedar (*Tamarisk spp*.) was created across the 48 continental US states with an accuracy of 90% (Morisette et al. 2006). This was created by integrating field data with land cover data (MODIS, 1 km), NDVI data (250 m), and an Enhanced Vegetation Index using logistic regression modelling. Also at the national scale, the potential ranges of major plant invaders in South Africa were assessed using climatic envelope models for 71 invasive plants utilising known presence data collected by gridcells (approximate 25 km x 25 km) across the country and variables such as growth days per year and mean annual precipitation (Rouget et al. 2004). At the landscape scale, in a retrospective study in New South Wales, Australia, the location of locust infestations (*Chortoicetes terminifera*) was successfully determined using habitat type and soil type and condition derived from Landsat multispectral scanner (MSS) data, which provided a useful tool for predicting breeding sites in the future (Bryceson 1991). In freshwater systems, a study classified submerged and emergent vegetation from colour infrared aerial photography over 12 years and in conjunction with other data on bathymetry, herbicide application, nutrient levels and turbidity was able to relate the distribution of aquatic vegetation and environmental factors, producing an inexpensive tool for resource management (Welch et al. 1988).

An alternative approach to species by species modelling is to identify hotspots of invasion for multiple species. A collaborative effort between NASA and the US Geological Survey is combining vegetation plot data with coarse scale remotely sensed information and geostatistical modelling to determine hotspots of invasive plant richness after a wildfire in New Mexico, USA (Schnase 2003).

11.6 Indirect Identification of Areas Vulnerable to Invasion

The approaches described in this section apply to IAS which occur in open areas and largely dominate the vegetation canopy. However, there are a number of other landscape and site features which can be detected by remote sensing which can assist in indicating the vulnerability of an area to invasion. Remote sensing can be used to identify areas of inappropriate grazing levels which can result in plant invasions through a combination of transporting propagules and micro-disturbance (although in some cases grazing also controls some IAS). In this case, imagery can be used to identify areas of reduced plant cover and soil and vegetation erosion. Second, detecting changes in the landscape over time can identify areas of disturbance which might be vulnerable to invasions. These include both natural disturbances such as landslides or the frequency or intensity of wildfire, or human-related such as trails, tracks and roads expanding into natural areas. Third, fragmentation of the natural habitat results in edge habitats being more vulnerable to invasion by plants and animals than core habitats (Hobbs 1998). The spatial distribution of natural habitats in the imagery and fragmentation indices can help identify vulnerable areas.

11.7 Limitations of Remote Sensing and Modelling Applications to Invasive Alien Species

11.7.1 Limitations for Remote Sensing Detection

Utilising remote sensing to identify invasive plant species suffers from many of the same caveats as using imagery to map other land cover features. First, the cost of data as well as the necessary software and hardware to support them is high, particularly for the newer forms of high spatial and spectral resolution imagery, although the overall trend is towards declining imagery costs (Turner et al. 2003). Second, the technical expertise required for processing both aerial photography (expert interpretation) and hyperspectral imagery (image processing) are high, with processing techniques for hyperspectral data still in the research and development phase. Third, the ability to detect IAS and the accuracy with which detection can be achieved varies among ecosystems, for example, identifying invasive plants in freshwater systems is challenging compared to terrestrial systems since submerged species are difficult to distinguish from water when present at low density and water turbidity from sediment and/or algae can mask detection (Underwood et al. 2006). Finally, while remote sensing techniques permit greater efficiency, they can never entirely replace *in situ* field measurements. The best results generally occur when both field data and imagery are used together with field measurements providing critical inputs for classifying and validating image classifications. Analyses are also significantly improved by a realistic understanding of, and familiarity with, the habitat particularly because of changes that can occur with the plant life cycle and the implications of these on spectral properties.

Despite these limitations, remote sensing is the only method for efficiently collecting information over large spatial extents at high spatial resolution and with 100% spatial sampling. In the future, developments in remote sensing data such as the increasing temporal frequency of image acquisition, techniques which fuse both passive and radar sensors, and the use of thermal image and texture analysis are likely to increase the tools available for mapping IAS. Furthermore, the synoptic view of imagery means lands in both public and private land ownership can be examined and analysed as a continuous landscape, thus facilitating an understanding of how land use may interact with the spread of invasives. Tradeoffs between image resolution and costs are rapidly changing as these technologies mature and more data providers are available. Policies governing access to original data also continue to evolve, for example, in the distribution of US governmental satellite data the benefits of increased imagery requires organized, searchable, and well-documented libraries of processed imagery and models.

11.7.2 Limitations for Predictive Models

Predictive models are valuable tools to inform decision making, however, there are a number of limitations. One of the obvious concerns regarding the output of species models is that predictions might over- or under-estimate the potential distribution of the target IAS. Over-prediction of distributions may result from identifying potential niche areas to which species may be unable to disperse (Peterson & Vieglais 2001), while under-prediction might result from insufficient explanatory variables used to correlate with the species occurrence. Furthermore, other data relevant for determining the spread of IAS—such as propagule pressure which determines the ease with which invasive plants overcome environmental barriers to become established (Rouget & Richardson 2003)—are generally not included. Second, predictive models are often static and fail to incorporate ecological processes and disturbances that might facilitate invasion, e.g., fire history or flood regimes. Finally, where known presence data are used, this is often based on a limited number of field collected data points within a discretely defined area, which is often at a finer spatial resolution than the selected explanatory data layers. To model at national or global spatial scales, occurrence data of the species across the range of explanatory variables are required.

Nonetheless, future research should emphasize the development of predictive models that incorporate remote sensing, environmental data and GIS techniques as a time and cost efficient method of identifying areas vulnerable to invasion. These approaches are particularly valuable for land managers with limited resources for monitoring and controlling IAS. Alternatively, predictive models can be used in aiding prevention of invasives by prioritizing species for which in-depth risk analyses should be undertaken. In both cases, results from models can aid the development of proactive policies at the national scale to restrict importation of high-risk IAS.

11.8 Data and Other Resources

The Global Invasive Species Programme (GISP)

http://www.gisp.org/index.asp

Aims include raising global awareness of the ecological and socio-economic impacts of IAS by developing a global information system on IAS, disseminating information on the impacts of invasives, providing information and training, and building international networks to achieve this.

The Global Invasive Species Database (GISD)

http://www.issg.org/database/welcome/

The GISD was developed as part of the global initiative on IAS led by the Global Invasive Alien Species Programme. It aims to increase public awareness about IAS to facilitate effective management and contains information on the ecology, impacts, distribution and pathways of IAS.

The Global Invasive Species Information Network (GISIN)

http://www.gisinetwork.org/

GISIN was formed to provide a platform for sharing IAS information at a global level, via the Internet and other digital means. Activities include developing a pilot system to search across diverse IAS information systems that are already present on the Internet.

A Weed Managers Guide to Remote Sensing and GIS

http://www.fs.fed.us/eng/rsac/invasivespecies/

The website provides technical information and guidance to help resource managers learn to use remote sensing and GIS to map, monitor and predict invasions.

The Nature Conservancy: Global Invasive Species Network

http://tncweeds.ucdavis.edu/remotesensing.html

The website reviews remote sensing and GIS technologies for detecting invasive species, particularly in their natural environment.

Weed Invasion Susceptibility Prediction

http://w3.uwyo.edu/~annhild/WISP/WISP1.html

The website provides an extension that can be used with GIS software (ArcView) to predict areas susceptible to invasion by IAS and also their predicted spread over time.

Invasive Species Forecasting System

https://bp.gsfc.nasa.gov/

NASA and US Geological Survey are developing a forecasting system for the early detection, remediation, management, and control of invasive species

Acknowledgements

We wish to acknowledge sponsors of several projects of the Center for Spatial Technologies and Remote Sensing (CSTARS) which are cited in this chapter including the Strategic Environmental Research and Development Program (SERDP) joint DOD/EPA/DOE conservation program for grant "Application of hyperspectral techniques to monitoring and management of invasive weed infestation", the NSF Complex Systems program "Dynamics of an invasive non-native species. Predicting and understanding spread and its impacts, biological, physical and human: the case of *Spartina alternaflora* in the western US", and the NASA/EPA STAR program for biological indicators of wetland ecosystems health, the "Western Center for Estuarine Ecosystem Indicator Research", and the NSF IGERT Training grant "Biological Invasions: From genes to ecosystems, from science to society", and lastly the NASA Airborne Science program at the Jet Propulsion Laboratory for support in collection of AVIRIS datasets and the HyVista Corporation for HyMap data used in this chapter.

11.10 References

Anderson, G. L., J. H. Everitt, A. J. Richardson, and D. E. Escobar. 1993. Using satellite data to map false broomweed (*Ericameria austrotexana*) infestations on south Texas rangelands. Weed Technology 7:865– 871.

Andrew, M. E., and S. L. Ustin. 2006. Spectral and physiological uniqueness of perennial pepperweed (*Lepidium latifolium*). Weed Science 54:1051-1062.

Asner, G. P., and P. M. Vitousek. 2005. Remote analysis of biological invasion and biogeochemical change. Proceedings of the National Academy of Sciences of the United States of America 102:4383-4386.

Besag, J. 1977. Some methods of statistical analysis for spatial data. Bulletin of the International Statistical Institute 47:77-92.

Bryceson, K. P. 1991. Likely locust infestation areas in western New South Wales, Australia, located by satellite. Geocarto International 6:21-37.

Budd, J. W., T. D. Drummer, T. F. Nalepa, and G. K. Fahnenstiel. 2001. Remote sensing of biotic effects: zebra mussels (*Dreissena polymorpha*) influence on water clarity in Saginaw Bay, Lake Huron. Limnology and Oceanography 46:213-223.

Crossman, N. D., and J. Kochergen. 2002. Mapping environmental weeds in the Mount Lofty Ranges, South Australia, using high resolution infrared aerial photography. Pages 1-4 in H. Spafford Jacob, J. Dodd, and J. H. Moore, editors. Proceedings of the thirteenth Australian weeds conference. Plant Protection Society of Western Australia, Perth, Australia.

Elvidge, C. D. 1990. Visible and near infrared reflectance characteristics of dry plant materials. International Journal of Remote Sensing of Environment 11:1775–1795.

Everitt, J. H., G. L. Anderson, D. E. Escobar, M. R. S. Davis, N. R., and R. J. Andrascik. 1995. Use of remote sensing for detecting and mapping leafy spurge (*Euphorbia esula*). Weed Technology 9:599-609.

Everitt, J. H., D. E. Escobar, M. A. Alaniz, M. R. Davis, and J. V. Richerson. 1996. Using spatial information technologies to map Chinese tamarisk (*Tamarix chinensis*) infestations. Weed Science 44:194-201.

Ford, G. E., and C.I. Zanelli. 1985. Analysis and quantification of errors in the geometric correction of satellite images. Photogrammetric Engineering & Remote Sensing 51.

Fuentes, D. A., J. A. Gamon, H. L. Qiu, D. A. Sims, and D. A. Roberts. 2001. Mapping Canadian boreal forest vegetation using pigment and water absorption features derived from the AVIRIS sensor. Journal of Geophysical Research 106:33565-33577.

Green, D. R., and S. Hartley. 2000. Integrating photointerpretation and GIS for vegetation mapping: some issue of error. Pages 103-134 in R. Alexander, and A. C. Millington, editors. Vegetation Mapping: From Patch to Planet. John Wiley & Sons Ltd, Chichester, U.K.

Hobbs, R. J. 1998. Impacts of land use on biodiversity in southwestern Australia. Pages 81-106 in P. W. Rundel, G. Montenegro, and F. M. Jaksic, editors. Landscape Disturbance and Biodiversity in Mediterranean-Type Ecosystems. Springer-Verlag, Berlin.

Hunt, R., R. Hamilton, and J. Everitt. 2005. A weed manager's guide to remote sensing and GIS (rsac-0077). Mapping weed infestations using remote sensing http://www.fs.fed.us/eng/rsac/invasivespecies/documents/mapping.pdf Pages 1-8.

Johnson, D. E. 1999. Surveying, mapping, and monitoring noxious weeds on rangelands. Pages 19-35 in R. L. Sheley, and J. K. Petroff, editors. Biology and management of noxious rangeland weeds Oregon State University Press, Corvallis, Oregon.

Joshi, C., J. de Leeuw, J. van Andel, A. K. Skidmore, H. D. Lekhak, I. C. van Duren, and N. Norbu. 2006. Indirect remote sensing of a cryptic forest understory invasive species. Forest Ecology and Management 225:245-256.

Joshi, C., J. de Leeuw, and I. C. van Duren. 2004. Remote sensing and GIS applications for mapping and spatial modelling of invasive species. Pages 669-677. Proceedings for ISPRS, Istanbul, Turkey.

Maheu-Giroux, M., and S. de Blois. 2005. Mapping the invasive species *Phragmites australis* in linear wetland corridors. Aquatic Botany 83:310-320.

Miao, X., P. Gong, S. Swope, R. L. Pu, R. Carruthers, G. L. Anderson, J. S. Heaton, and C. R. Tracy. 2006. Estimation of yellow starthistle abundance through CASI-2 hyperspectral imagery using linear spectral mixture methods. Remote Sensing of Environment 101:329-341.

Mooney, H. A., and E. E. Cleland. 2001. The evolutionary impact of invasive species. Proceedings of the National Academy of Sciences 98:5446-5451.

Morisette, J. T., C. S. Jarnevich, A. Ullah, J. Cai W, J. A. Pedelty, J. E. Gentle, T. J. Stohlgren, and J. L. Schnase. 2006. A tamarisk habitat suitability map for the continental United States. Frontiers in Ecology and the Environment 4:11-17.

Mulitsch, M., and S. L. Ustin. 2003. Mapping invasive plant species in the Sacramento-San Joaquin Delta region using hyperspectral imagery. Report to the California Department of Boating and Waterways. Center for Spatial Technologies and Remote Sensing, University of California, Davis, Sacramento, California.

Orth, R. J., and K. A. Moore. 1983. Submerged vascular plants: techniques for analysing their distribution and abundance. Marine Technology Society Journal 17:38-52.

Pauchard, A., and K. Shea. 2006. Integrating the study of non-native plant invasions across spatial scales. Biological Invasions 8:399-413.

Penuelas, J., J. Pinol, R. Ogaya, and I. Filella. 1997. Estimation of plant water concentration by the reflectance Water Index WI (R900/R970). International Journal of Remote Sensing 18:2869-2875.

Peters, A. J., B. C. Reed, M. D. Eve, and K. C. McDaniel. 1992. Remote sensing of broom snakeweed (*Gutierrezia sarothrae*) with NOAA-10 spectral image processing. Weed Technology 6:1015–1020.

Peterson, A. T., and D. A. Vieglais. 2001. Predicting species invasions using ecological niche modeling: new approaches from bioinformatics attack a pressing problem. BioScience 51:363-371.

Pimentel, D., R. Zuniga, and D. Morrison. 2005. Update on the environmental and economic costs associated with alien-invasive species in the United States. Ecological Economics 52:273-288.

Richardson, D. M., P. Pysek, M. Remanek, M. G. Barbour, F. D. Panetta, and C. J. West. 2000. Naturalization and invasion of alien plants: concepts and definitions. Diversity and Distributions 6:93-107.

Rosso, P. H., S. L. Ustin, and A. Hastings. 2005. Use of lidar to study changes associated with *Spartina* invasion in San Francisco Bay marshes. Remote Sensing of Environment 100:295-306.

Rouget, M., and D. M. Richardson. 2003. Inferring process from pattern in plant invasions: A semimechanistic model incorporating propagule pressure and environmental factors. American Naturalist 162:713-724.

Rouget, M., D. M. Richardson, J. L. Nel, D. C. Le Maitre, B. Egoh, and T. Mgidi. 2004. Mapping the potential ranges of major plant invaders in South Africa, Lesotho and Swaziland using climatic suitability. Diversity and Distributions 10:475-484.

Rowlinson, L. C., M. Summerton, and F. Ahmed. 1999. Comparison of remote sensing data sources and techniques for identifying and classifying alien invasive vegetation in riparian zones. Water SA 25:497-500.

Sanderson, E. W., M. Zhang, S. L. Ustin, and E. Rejmankova. 1998. Geostatistical scaling of canopy water content in a California salt marsh. Landscape Ecology 13:79–92.

Schnase, J. L. 2003. Invasive species forecasting system. Test site – Cerro Grande Wildfire Site. http://invasivespecies.gsfc.nasa.gov/isfs_cerro.html. NASA/GSFC.

Stow, D., A. Hope, D. Richardson, D. Chen, C. Garrison, and D. Service. 2000. Potential of colour-infrared digital camera imagery for inventory and mapping of alien plant invasions in South African shrublands. International Journal of Remote Sensing 21:2965 – 2970.

Thenkabail, P. S. 1999. Characterization of the alternative to slash-and-burn benchmark research area representing the Congolese rainforests of Africa using near-real-time SPOT HRV data. International Journal of Remote Sensing 20:839-877.

Thuiller, W., D. M. Richardson, P. Pysek, G. F. Midgley, G. O. Hughes, and M. Rouget. 2005. Niche-based modelling as a tool for predicting the risk of alien plant invasions at a global scale. Global Change Biology 11:2234-2250.

Turner, W., S. Spector, N. Gardiner, M. Fladeland, E. Sterling, and M. Steininger. 2003. Remote sensing for biodiversity science and conservation. Trends In Ecology & Evolution 18:306-314.

Underwood, E. C., M. J. Mulitsch, J. A. Greenberg, M. L. Whiting, S. L. Ustin, and S. C. Kefauver. 2006. Mapping invasive aquatic vegetation in the Sacramento-San Joaquin Delta using hyperspectral imagery. Environmental Monitoring and Assessment 121:47-64.

Underwood, E. C., S. L. Ustin, and C. M. Ramirez. 2007. A comparison of spatial and spectral image resolution for mapping invasive plants in coastal California. Journal of Environmental Management 39:63-83.

Venugopal, G. 1998. Monitoring the effects of biological control of water hyacinths using remotely sensed data: a case study of Bangalore, India. Singapore Journal of Tropical Geography 19:92-105.

Walsh, S. J., D. R. Lightfoot, and D. R. Butler. 1987. Recognition and assessment of error in Geographic Information System. Photogrammetric Engineering and Remote Sensing 53:1423-1430.

Welch, R., M. Remillard, and R. B. Slack. 1988. Remote sensing and geographic information system techniques for aquatic resource evaluation. Photogrammetric Engineering & Remote Sensing 54:177-185.

Appendices

COMPILER: Ned Horning (Center for Biodiversity and Conservation of the American Museum of Natural History)

A.1 Abbreviations and Acronyms

This list includes acronyms common in remote sensing, and others included in this sourcebook. A more complete remote sensing acronym reference can be found in "Glossary of remote sensing terms" section of the Canada Centre for Remote Sensing web site: http://ccrs.nrcan.gc.ca/.

ADEOS	Advanced Earth Observation System
AIRS	Atmospheric Infrared Sounder
AIRSAR	Airborne Synthetic Aperture Radar
ALI	Advanced Land Imager (on EO-1 satellite)
ALOS	Advanced Land Observing Satellite
ASAR	Envisat Advanced Synthetic Aperture Radar
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
AVHRR	Advanced Ver y High-Resolution Radiometer
BRDF	Bidirectional Reflectance Distribution Function
CASI	Compact Airborne Spectrographic Imager
CEOS	Committee on Earth Observation Satellites
CIR	Colour Infrared
DEM	Digital Elevation Model
DN	Digital Number (pixel value)
DTM	Digital Terrain Model
EMR	Electromagnetic Radiation
EMS	Electromagnetic Spectrum
ENVISAT	Environmental Satellite
EOS	Earth Observing System
EOSP	Earth Observing Scanning Polarimeter
ERS-1	Earth Remote Sensing Satellite
ERTS	Earth Resources Technology Satellite
ETM	Enhanced Thematic Mapper
FFT	Fast Fourier Transform
FIR	Far Infrared
FOV	Field of View
GCP	Ground Control Point
GIS	Geographic Information System
GMS	Geostationary Meteorological Satellite
GOES	Geostationary Operational Environmental Satellite
GPS	Global Positioning System
HIRS	High-Resolution Infrared Sounder
HIS	Hue, Intensity, Saturation
IKONOS	A commercial satellite operating at one (panchromatic) / four (multispectral) metre resolution
IRS	Indian Remote Sensing Satellite

IUCN	World Conservation Union
JAXA	Japan Aerospace Exploration Agency
JERS	Japanese Earth Resources Satellite
LAI	Leaf Area Index
LIDAR	Light Detection and Ranging
LUT	Look-up Table
LWIR	Long-Wave Infrared
MISR	Multi-Angle Imaging SpectroRadiometer
MLS	Microwave Limb Scanner
MODIS	Moderate Resolution Imaging Spectroradiometer
MSS	Multispectral Scanner
NASA	National Aeronautics and Space Administration
NDVI	Normalized Difference Vegetation Index
NIR	Near Infrared
NOAA	National Oceanographic and Atmospheric Administration
PCA	Principal Component Analysis
RADAR	Radio Detection and Ranging
Radarsat	Radar Satellite
RGB	Red, Green, Blue
SAGE III	Stratospheric Aerosol and Gas Experiment III
SAR	Synthetic Aperture Radar
SIR-C	Shuttle Imaging Radar-C
SPOT	Système Pour l'Observation de la Terre
SRTM	Shuttle Radar Topography Mission
SWIR	Short-Wave Infrared
TES	Tropospheric Emission Spectrometer
TIMS	Thermal Infrared Multispectral Scanner
TIR	Thermal Infrared
TM	Thematic Mapper
TOMS	Total Ozone Mapping Spectrometer
TOPEX	Ocean Topography Experiment
TOPSAR	Topographic Synthetic Aperture Radar
TRMM	Tropical Rainfall Measurement Mission
UNEP-WCMC	UNEP World Conservation Monitoring Centre
UV	Ultraviolet
VIS	Visible Spectrum
WFOV	Wide Field Of View
WCPA	World Consortium on Protected Areas
WDPA	World Database of Protected Areas
WWF	World Wide Fund for Nature
X-SAR	X-Band Synthetic Aperture Radar

A.2 Glossary

The definitions in this glossary are relevant to remote sensing applications. Some of these terms have broader definitions than the one given. An extensive glossary for remote sensing terms can be found on the Canada Centre for Remote Sensing website: http://www.ccrs.nrcan.gc.ca/.

Active sensor | Remote sensing instrument that emits its own energy and then measures that energy after it is reflected from features on the Earth's surface.

Band | A single layer of an image created using a specific range of wavelengths. A colour digital image is composed of three bands that record red, green, and blue wavelengths of light.

Channel | This is typically synonymous with "band".

Classification | The process of identifying and labelling features in an image. Pixels are grouped into categories using manual or automated methods.

Covariance | The extent to which two random variables vary together. A positive covariance indicates that a higher value of one variable tends to be linked to a higher value of another. Negative covariance indicates that a higher value of one variable tends to be linked to a lower value in another. This value is used when comparing two different bands of the same image to identify areas of consistent land cover or habitat.

Electromagnetic Spectrum | The range of wavelengths of electromagnetic radiation. Remote sensing applications typically use wavelengths that include the visible wavelengths (blue through red), the infrared, and microwave regions of the electromagnetic spectrum. The shorter wavelength ultraviolet, x-ray, and gamma rays are not typically used. The long wavelength radio waves are also not typically used.

Feature recognition | The ability to identify a feature on a digital image. In remote sensing this can refer to identifying manmade features such as buildings or airplanes but it can also refer to natural features such as land cover or topographic features such as ridges and valleys.

Hyperspectral | Many bands (often more than 100). Some hyperspectral sensors are capable of recording images with more than 200 bands and each band represents a specific (usually very narrow) portion of the electromagnetic spectrum.

Infrared | The portion of the electromagnetic spectrum that lies between the visible and microwave wavelengths (0.7 nanometres – 100 micrometres).

Lidar | Lidar is an acronym for Light Detection and Ranging (LIDAR – although the letters are usually not capitalized). It is a remote sensing instrument that emits a laser pulse and measures the time for the pulse to return to the detector as well as the intensity of the returned signal. Interpreting the returned signal can provide digital elevation models (DEMs), and height and structure information about vegetation and other features.

Mosaicking | The process of combining several neighbouring images together. This can be undertaken for display or analysis purposes although can introduce errors when classifying as each individual image has been acquired under slightly different environmental conditions.

Multispectral | Multiple bands, with each band recording a different portion of the electromagnetic spectrum.

Open source software | Software that has the source code freely available and is licensed so that it can be freely distributed and modified as long as appropriate credit is provided to the developers. There are several licensing options for open source software but all of them follow these basic rules. More information about open source software is available at the Open Source Initiative web page (http://

www.opensource.org/). More information about open source geospatial software can be found at the Open Source Geospatial (OSGeo) website: http://www.osgeo.org/.

Optical sensor | Sensor that is sensitive to visible and infrared wavelengths of light.

Panchromatic Band | A band available on some sensors that records information across a wide range of the electromagnetic spectrum. This band is often recorded at a higher spatial resolution and can be used to sharpen data across the other bands.

Passive sensor | Remote sensing instrument that measures energy that originated from the sun and was reflected by the Earth's surface or was emitted from features on the Earth's surface.

Pixel | An individual "picture element" from an image. When an image is magnified the individual pixels can be seen as a square or rectangular block in the image.

Radar | Radar is an acronym for Radio Detection and Ranging (RADAR – although the letters are usually not capitalized). It is a remote sensing instrument that emits a microwave signal and measures the time for the signal to return to the detector as well as the intensity of the returned signal. Interpreting the returned signal can provide digital elevation models (DEMs), changes in water level and information about land cover.

Radiance | Measure of radiation energy. Radiance is usually measured in watts per unit solid angle area.

Radiation | Energy transferred as particles or waves through space or other media. In remote sensing radiation often comes from the sun although it can also come from the sensor as is the case with LIDAR and RADAR sensors.

Radiometer | An instrument that measures the intensity of electromagnetic energy in different wavelengths.

Reflectance | Ratio of the intensity of reflected radiation to that of incident radiation on a surface. Reflectance is expressed in percent and usually refers to a specific wavelength.

Resolution | The smallest detail visible in an image. Usually resolution refers to spatial resolution. The spatial resolution of an image is an indication of the size of a single pixel in ground dimensions. It is usually presented as a single value that represents the length of one side of a square. For example, a spatial resolution of 30 metres means that one pixel represents an area 30 metres by 30 metres on the ground. If the pixel is rectangular, it will be recorded as a height and width dimension (i.e., 56m x 79m).

Sensor | A device that is capable of recording the intensity of electromagnetic radiation. In remote sensing these devices typically record this information in images, rather than from a single point.

Spectral reflectance curve | A curve describing the reflectance values for a particular feature over a range of wavelengths. The x-axis is for wavelength and the y-axis is for reflectance. Different features have unique spectral reflectance curves.

Visible spectrum | The portion of the electromagnetic spectrum between the ultraviolet and infrared wavelengths. This is the range of wavelengths (including the colours in the spectrum from blue through red) that can be detected by the human eye.

Wavelength | Distance between two crests of a wave. In remote sensing electromagnetic waves are typically measured in nanometres, millimetres, and centimetres.

A.3 Satellites, sensors and data

A.3.1 Sensor characteristics and image selection

Selecting the right imagery for a particular task can seem very complex. However, with a little background information and practice it is possible to narrow the choice to just a few of the dozens of image types. It can also be very helpful to discuss the question with other users who have addressed similar issues. Remote sensing resources on the Internet such as e-mail list servers or contacts with a university or other organization working with satellite imagery, can provide valuable advice for selecting appropriate imagery.

Often the most limiting factor is the money available to purchase imagery. The price for satellite imagery can range from nothing to over $50/square kilometre. The pricing schemes used by the various vendors change and they can be a little difficult to understand. It is always a good idea to look at the vendor's web site or to contact the vendor to find out how their products are priced. There are some great archives offering free satellite imagery, but most of that imagery is either from the Landsat series of satellites or it is coarse (less the 250m resolution) resolution.

Spatial resolution

This refers to the size of a pixel in terms of ground dimensions. It is usually presented as a single value that represents the length of one side of a square. For example, a spatial resolution of 30 metres means that one pixel represents an area of 30 metres by 30 metres on the ground. If the pixel is rectangular it will be represented by a height and width dimension (i.e., 56m x 79m).

So, how does one select an appropriate spatial resolution? Although there are guidelines for selecting an appropriate spatial resolution most people rely on experience, and trial and error. If you can't tap into someone with sufficient experience try to select a resolution that is a factor of 10 times smaller than the size of the features you are identifying. For example, if you want to visually delineate features with a minimum size (minimum mapping unit) of 1 hectare (100m x 100m), a 30m spatial resolution is probably sufficient but if you want to identify tree crowns that are roughly 3m x 3m you would probably want to select a 1m or finer resolution.

In the remainder of this section other variables associated with different satellite image products will be described to assist in deciphering information provided by vendors.

Spectral bands (channels)

When evaluating the spectral quality of a particular image product there are three variables that are usually considered:

- bandwidth,
- band placement, and
- the number of bands.

The **spectral bandwidth** refers to the range of wavelengths that are detected by a particular sensor. This characteristic is particularly important when using hyperspectral imagery.

Band placement defines the portion of the electromagnetic spectrum that is used for a particular image band. For example, one channel might detect blue wavelengths and another channel might detect thermal wavelengths. The particular properties of the features you are interested in dictate which bands are important.

The last spectral variable is the **number of bands**. This is generally less important for visual interpretation, which tends to use only three bands at a time, but can become very important when using automated classification approaches. Hyperspectral images are those with many bands (usually over 100).

Program history

It is important to know the background of a satellite sensor (or its program history) if you want to be able to obtain imagery that was acquired several years ago. Some satellite image programs, such as Landsat, were started over 30 years ago whereas others, such as Quickbird, started in 2001.

Image surface area

The ground area covered by an image product defines the footprint of the image. Usually, high spatial resolution images cover less ground per image than the lower resolution images but this is not always the case. Having images that cover large areas increases your chances of covering your area of interest in the fewest number of scenes possible. Stitching together adjacent images can be problematic, especially if the adjacent images were acquired during different seasons. Having your entire study area on a single image saves a lot of work.

Multi-angle options

Some satellite sensors can be pointed over a particular target area to acquire images. This has a few benefits. One is that a user can request that a particular feature be targeted thereby removing the problem of having to stitch adjacent images together since your study area can be placed in the middle of the image. Another advantage of pointable sensors is that they can be used to acquire stereo imagery which can be viewed in 3-D and can be used to create Digital Elevation Models (DEMs). Other sensors that are not pointable (they always point straight down) usually use a systematic, predefined acquisition program that always acquires imagery over the same area. An example of this is the Landsat World Reference System (WRS) index that breaks up the globe into overlapping "tiles." These tiles each have unique reference numbers known as the "path" and "row." Knowing the path and row numbers makes it easy to search for all of the images available for your area of interest.

Repeat interval

The repeat interval is the minimum time a particular feature can be recorded twice. For example, with Landsat the same image area can be recorded every 16 days. Some sensors with a very wide field of view can acquire multiple images of the same area in the same day. Another advantage of pointable sensors is that they can reduce the repeat time for which a feature can be recorded because they are not limited to viewing directly under the satellite.

It should also be noted that most remote sensing satellites have a near-polar orbit and are not able to acquire imagery at the poles since their orbit does not go over these areas.

Scheduling options and price

In many cases you can find appropriate imagery in an archive. However, if it is necessary to request new imagery for a particular area it is important to know what scheduling options exist and their associated costs. Most of the commercial providers have multiple scheduling options depending on the priority. High priority scheduling can cost several thousand dollars per image in addition to the image costs. Always check with the vendor to find out how their scheduling works and how much it costs.

Selecting imagery over an area of interest

Each of the image vendors and most of the image archives have some sort of browse facility that allows you to select the area you are interested in with links to browse images that show you what the image looks like before you purchase it. Some of the browse facilities use an interactive map that you can use to zoom in on and outline your area. Others let you specify the area using latitude and longitude coordinates. Many of the sites give you both map and coordinate options. Much effort has gone into improving the user interface for these sites and these days they are generally pretty straight forward to use with many providing short tutorials on how to use the browse facility.

A.3.2 Sensors commonly used to assess biodiversity issues

Below is a list of some of the common satellite sensors used in biodiversity conservation. The list is ordered from fine to coarse resolution with optical sensor and radar sensors at the end. The satellite name is indicated the left/sensor on the right.

IKONOS-2

URL: http://www.geoeye.com/products/default.htm
Spatial resolution: Panchromatic: 1m, Multispectral; 4m
Image coverage: 11.3 km swath width
Spectral bands: 1 Panchromatic: 525.8-928.5nm; 4 Multispectral: 450-520, 520-600, 630-690, 760-900nm
Repeat frequency: 1 – 3 days
Launch date: 1999

QUICKBIRD

URL: http://www.digitalglobe.com/
Spatial resolution: Pan: 61 cm; MS: 2.44 m
Image coverage: 16.5 km
Spectral bands: Pan: 725, 479.5, 546.5, 654, 814.5 nm
Repeat frequency: 1-3
Launch date: 2001

SPOT 5/HRG

URL: http://www.spotimage.fr
Spatial resolution: Panchromatic: 2.5m, Multispectral: 10m, SWIR: 20m
Image coverage: 60km x 60km to 80km
Spectral bands: 1 Panchromatic: 480-710nm; 4 Multispectral: 500-590, 610-680, 780-890, 1580-1750nm
Repeat frequency: 2-3 days
Launch date: 2002

RESOURCESAT 1 IRS/P6 (three instruments LISS-3, LISS-4, and AWiFS)

URL: http://www.isro.org/pslvc5/index.html
Spatial resolution: LISS-3: 23.5m, LISS-4: 5.8m, AWiFS 56m.
Image coverage: LISS-3: 141km swath, LISS-4: 23.9 km (MX mode) 70.3m (Pan mode), AWiFS 740km.
Spectral bands: LISS-3 and AWiFS: 520-590, 620-680, 770-860, 1550-1700
LISS-4: 520-590, 620-680, 770-860
Repeat frequency: LISS-4: 5 days, LISS-3 and AWiFS: 24 days
Launch date: 1996, 2003

SPOT 4/HRVIR

URL: http://www.spotimage.fr
Spatial resolution: Panchromatic 10m, Multispectral 20m, SWIR 20 m
Image coverage: 60km x 60km to 80km
Spectral bands: 1 Panchromatic: 610-680nm, 4 Multispectral: 500-590, 610-680,780-890, 1580-1750nm
Repeat frequency: 2-3 days
Launch date: 1998

IR-MSS/CBERS2, 2b

URL: www.cbers.inpe.br/en/programas/cbers1-2.htm and www.cast.cn
Spatial resolution: 20m
Image coverage: 113km
Spectral bands: VIS: 0.45-0.52µm, 0.52-0.59µm, 0.63-0.69µm, NIR: 0.77-0.89µm, PAN: 0.51-0.71µm Repeat frequency: 26 days
Launch date: 2003, 2006

Terra/ASTER

URL: http://asterweb.jpl.nasa.gov/
Spatial resolution:Visible and near-infrared (VNIR): 15m, Shortwave infrared (SWIR): 30m, and Thermal infrared (TIR): 90m.
Image coverage: 60mk x 60km
Spectral bands: 4 VNIR: 520-600, 630-690, 780-860, 780-860 nm (last band is pointed aft)
6 SWIR: 1600-1700, 2145-2185, 2185-2225, 2235-2285, 2295-2365, 2360-2430nm
5 TIR: 8125-8475, 8475-8825, 8925-9275, 10250-10950, 10850-11650 nm
Repeat frequency: 16 days; acquisitions are scheduled
Launch date: 2000

Landsat/TM and ETM+

URL: http://edc.usgs.gov/guides/landsat_tm.html and http://landsat.usgs.gov/project_facts/history/landsat_7.php
Spatial resolution: Panchromatic: 15m, Multispectral: 30m Thermal: 60
Image coverage: 185km x 170km
Spectral bands: 1 Panchromatic (only on ETM+): 520-730nm
7 Multispectral: 450-520, 520-600, 630-690, 760-900, 1550-1750, 10400-12500, 2080- 2350nm
Repeat frequency: 16 days
Launch date: Landsat TM 4 and 5 1982 and 1984, Landsat ETM+ 1999

Landsat/MSS

URL: http://edc.usgs.gov/guides/landsat_mss.html
Spatial resolution: Landsat 1-3: 56m x 79m, Landsat 4-5: 68m x 82m
Image coverage: 185km x 185km
Spectral bands: 4-5 Multispectral: 500-600, 600-700, 700-800, 800-1100, 10400-12600nm (only on Landsat 1-3)
Repeat frequency: Landsat 1-3: 18 days,
Landsat 4-5: 16 days
Launch date: 1972, 1975, 1978, 1982, 1984

ENVISAT-1/MERIS

URL: http://earth.esa.int/dataproducts/
Spatial resolution: Ocean: 1040m x 1200 m, Land & coast: 260m x 300m
Image coverage: 1150km
Spectral bands: VIS-NIR: 15 bands selectable across range: 0.4-1.05µm (bandwidth programmable between 0.0025 and 0.03µm)
Repeat frequency: 3 days
Launch date: 2002

Terra/MODIS

URL: http://modis.gsfc.nasa.gov/
Spatial resolution: Bands 1 and 2: 250m, Bands 3-7: 500m, and Bands 8-36: 1km
Image coverage: 2330 km swath width
Spectral bands: Bands 1 and 2: 620-670, 841-876
Bands 3-7: 459-479, 545-565, 1230-1250, 1628-1652, 2105-2155nm
Bands 8-36: 12 bands ranging from 405-965nm and 17 bands ranging from 1360-14385nm
Repeat frequency: near daily
Launch date: 2000

NOAA KLM/AVHRR

URL: http://www2.ncdc.noaa.gov/docs/klm/index.htm
Spatial resolution: 1.1 km
Image coverage: 3000 km wide
Spectral bands: Multispectral: 580-680, 725-1000, 1580-1640, 3550-3930, 10300-11300, 11500-12500nm
Repeat frequency: 1 day
Launch date: 1978

SPOT VEGETATION

URL: http://www.spotimage.fr
Spatial resolution: 1.15km at nadir
Image coverage: 2200 km wide, variable length
Spectral bands: VIS: 0.61-0.68µm, NIR: 0.78-0.89µm, SWIR: 1.58-1.75µm
Repeat frequency: 1 day
Launch date: 1986

SeaWIFS

URL: http://oceancolor.gsfc.nasa.gov/SeaWiFS/BACKGROUND/
Spatial resolution: 1.1 km
Image coverage: 2,801 km
Spectral bands: 8 bands at 402-422, 433-453, 480-500, 500-520, 545-565, 660-680, 745-785, 845-885 nm
Repeat frequency: 1 day
Launch date: 1997

RADAR

ENVISAT/ASAR C-band

URL: http://earth.esa.int/dataproducts/
Spatial resolution: 150m x 150m
Image coverage: Image and alternating polarisation modes: up to 100km, Wave mode: 5km, Wide swath and global monitoring modes: 400km or more
Spectral bands: Microwave: C-band, with choice of 5 polarisation modes (VV, HH, VV/HH, HV/HH, or VH/VV)
Repeat frequency: 35 days; acquisitions are scheduled
Launch date: 2002

Radarsat-1/ SAR (Synthetic Aperture Radar) C-band (HH polarization)

URL: http://www.space.gc.ca/asc/eng/satellites/default.asp
Spatial resolution: Standard: 100km Wide: 150km, Fine: 45km, ScanSAR Narrow: 300km, ScanSAR Wide: 500km, Extended (H): 75km, Extended (L): 170km Image coverage: : Standard: 25 x28 m (4 looks), Wide beam (1/2):48-30 x 28m/ 32-25 x 28m (4 looks), Fine resolution: 11-9 x 9m (1 look), ScanSAR (N/W): 50 x 50m/ 100 x 100m (2-4/4-8 looks), Extended (H/L): 22-19x28m/ 63-28 x 28m (4 looks) Spectral bands: Microwave: C band: 5.3GHz, HH polarisation

Repeat frequency: 24 days
Launch date: 1995

ALOS (Advanced Land Observing Satellite)/ Phased Array type L-band Synthetic Aperture Radar (PALSAR)

URL: http://www.jaxa.jp/projects/sat/alos/index_e.html
Spatial resolution: Hi-res: 7-44m or 14-88m (depends on polarisation and looks), ScanSAR mode: <100m, Polarimetry 24-88m
Image coverage: High resolution mode: 70km, Scan SAR mode: 250-360km, Polarimetry: 30km
Spectral bands: Microwave: L-Band 1270MHz
Repeat frequency: 3 days
Launch date: 2006

For further information and comparison tables:

CEOS

A catalog of missions and satellite instruments from 2005 Edition of the CEOS Earth Observation Handbook, prepared by the European Space Agency (ESA).
http://www.eohandbook.com/eohb05/pdfs/miss_inst_2005.doc

ASPRS Guide to land Imaging Satellites

This PDF file is a complete overview of civil land imaging satellites with resolutions equal to or better than 36 metres in orbit or currently planned to be in orbit by 2010.
http://www.asprs.org/news/satellites/

ITC's database of satellites and sensors

A database with a broad range of information about most satellite remote sensing systems in use today. The database can be browsed and searched for information.
http://itc.eu/research/products/sensordb/searchsat.aspx

Earth observation satellites and sensors for risk management

A good resource for a broad range of information about different sensor systems and satellites. The site includes a table listing past and future launch dates as well.
http://www.space-risks.com/SpaceData/index.php?id_page=2

A.3.3 Continuity of present systems and useful new platforms

Operational monitoring for biodiversity indicators requires data for large areas, ideally available for little or no cost. While the U.S. Government continues to make available (through NASA and USGS) low- or no-cost data that are free of redistribution restrictions, the ability of national governments to sustain Earth-focused remote sensing research and related applications may be subject to change. So far, the Landsat-TM class of data has proven to be very useful because of its spatial and spectral resolutions and its availability. Other sensors collecting data of this type include IRS, SPOT IMAGE and CBERS and their importance for biodiversity information is heightened while near-term access to Landsat data remains an issue. Corona and other declassified sensors, which collected high resolution imagery prior to the launch of Landsat, with these data now being publicly available are important sources of data for extending the environmental record farther into the past.

The U.S. Government has committed to provide an operational Landsat continuity mission, but a launch date is not expected until mid-2011 at the earliest. Satellites or sensors that might potentially be available to fill the gap between Landsat 7 and its successor are IRS, CBERS, ASTER, and SPOT. Terra ASTER and the EO-1 ALI research sensors collect data available through well maintained archive and ordering systems at a low cost to the user. Terra MODIS collects data at coarser spatial resolutions (250 m, 500m, and 1000m) but with higher temporal availability due to possible repeat acquisitions every 1-2 days.

High-resolution imagery will continue to be important for local applications and as a surrogate for ground sampling. Occasionally these data come into the public domain through data buys or in response to humanitarian relief efforts. Aerial photography will always be an alternative and frequently a preferred data source for high resolution data.

In addition to these long-running programs several new programs began around the turn of the millennium and others are scheduled for launch in the near future. The ASPRS Guide to Land Imaging Satellites (http://www.asprs.org/news/satellites/) illustrates the timing and spatial resolution for several future missions. In the near future, 8 countries plan to operate satellites with 1 metre or better spatial resolution and roughly 20 countries will have operational optical satellites (K. Jacobsen, University of Hannover, Germany: ISPRS Hannover workshop 2005).

A.4 Three examples of how to obtain imagery

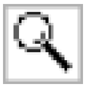
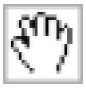
Below are guidelines for navigating three satellite image web archives.

A.4.1 GLCF Map Search http://glcfapp.umiacs.umd.edu:8080/esdi/index.jsp

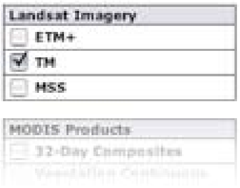
On the *map search* page, you will see a world map, you can choose the type of imagery you are interested in finding on the left, and click the *Update Map* button to see the areas that are available in red.

Step 1: Zoom In

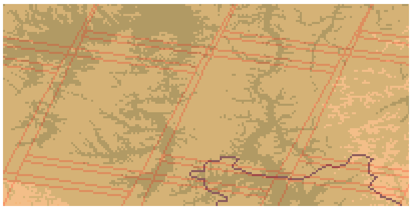
Zoom to your area of interest by clicking on the map. Above and to the left of the map are the zoom and pan buttons. The zoom bar is found centered above the map. These can be used in the following ways:

	ZOOM BUTTON: When this button is selected, clicking on the map will zoom in one level and re-center the map This button is selected, by default, when starting a new map session.	
	PAN BUTTON: Select this button if you want the map to pan to the location when clicking on the map. The map will re-center to the location clicked without changing the zoom level.	
	ZOOM BAR: Use this bar to zoom in or out to any level without re-centering the map. Clicking the plus button zooms in one level, the minus button zooms out one level. To zoom in or out to a specific level, click any of the bars between the plus and minus buttons. Click on the closest bar to the minus button to quickly zoom back out to the global level.	

Step 2: Select Datasets

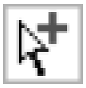
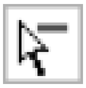
	Datasets are listed on the left hand side of the screen. Select the datasets that you are interested in and then click on  Areas covered by available data are shown on the map in a light red/orange color.	

Step 3: Make a Selection

	Make a selection by using any of the following methods: ■ Clicking on the map using the selection buttons ■ Selecting all items shown on the map ■ Querying by WRS Path/Row ■ Querying by Latitude/Longitude ■ Querying by Place Name ■ Drawing a rectangle, line, or polygon on the map	

Details on each of these methods are available. Selections are shown on the map with a thick yellow line. All scenes that match the current selection are shown in a darker color. Refine searches using parameters found under the "Date/Type" tab. Additional layers can be added to the map under the "Map Layers" tab. A selection cannot match more than 600 images; if your selection has more than this, refine your search until you have less than 600 images.

Selection Buttons

	SELECT BUTTON: When this button is selected, clicking on the map creates a selection around all data found at that point. Add more data to your selection by continuing to click on different points on the map.
	UNSELECT BUTTON: When this button is selected, clicking on the map removes all selections found at that point. Selections created by other methods (not using the select button) can also be unselected with this button.

Overlapping selections will have dissolved borders on the map. Using the unselect button requires selecting on both selections unless you click on the area where they overlap.

Step 4: Preview and Download

	Once you have data in your selection, the "Preview and Download" button will become active. You can then save your search in your workspace or begin downloading directly.

A.4.2 Global Visualization Viewer (GLOVIS) – http://glovis.usgs.gov/

You will see a similar map interface on the GLOVIS web site. There is a *Select Sensor* drop down menu where you will find the available data sets. Click the *About Browse Images* button to read more details about the available imagery.

Choose a latitude/longitude location, or simply click on the map to view the available imagery. Once you are in the viewer, you can change the *Sensor*, *Resolution* and *Map Layers* using the menu bar above the map.

For Landsat images, you should see nine images in an interactive mosaic in the viewer. You can click on any image to bring it to the top. To scan the different dates for this image, click the *Previous Scene* and *Next Scene* buttons on the left. You can also choose to exclude images based on the amount of cloud cover with the *Max Cloud* option.

Right clicking on an image brings up additional options such as viewing metadata, a preview image. Choose *add scene to list* for ordering. Clicking Order will bring you to the appropriate USGS web site for purchasing the image. You can either have disks mailed to you, or download via FTP.

A.4.3 Earth Explorer – http://edcsns17.cr.usgs.gov/EarthExplorer/

Choose Guest to enter the Data Set Selection menu, or register as a user for additional options such as saving search results.

In the Data Set Selection area you will find a list of the available data sources, as well as *Related Links* to additional information. Choose the data set that you would like to search. In the Spatial Coverage box you can define your area of interest on a map, using coordinates, or a place name. Click the *Continue* button to advance.

You can choose the (*Additional Search Criteria…)* link to limit the search by Path/Row, cloud cover, entity ID, day or night, or data classification for Landsat. You can also limit the search by choosing a date range in the *Acquisition Date* box. Choose a large number for records returned in order to view the complete range of available data. Click *Search* and wait for the results.

Once the results are returned, click the data set link to view the available images. Click the *Show* link to view preview images, metadata, and footprints. Not all datasets have preview images. Images can be ordered through the "Shopping Basket" feature.

A.5 Online tutorials and software resources

A.5.1 Tutorials

Studying Earth's Environment from Space

This is an educational site, sponsored by Old Dominion University, for high school and college instructors and students. Free data, image processing software, and tutorials are provided for the following themes: stratospheric ozone, global land vegetation, oceanography, and polar sea ice processes.

http://www.ccpo.odu.edu/SEES/

Remote Sensing Advanced Technology (RSAT) Tutorials

This site has a few simple examples of how remote sensing imagery can be used in a variety of applications. It illustrates the practical aspects of concepts such as pixel size, spectral band combinations, and 3-D perspective views.

http://www.rsat.com/tutorials.html

NASA Remote Sensing Tutorial

This is a fairly complete, traditional-style remote sensing tutorial available on CD and the Web. The contents could be used for a college-level introductory remote sensing course. It was developed and is currently supported by NASA. It is sometimes referred to as the "Short Tutorial" after the author, Dr. Nick Short.

http://rst.gsfc.nasa.gov/

Ohio U.-view Remote Sensing On-Line Tutorial

This is a Power Point style presentation of remote sensing. The tutorial covers a broad range of topics but does not provide significant detail on individual topics.

http://dynamo.phy.ohiou.edu/tutorial/tutorial_files/frame.htm

The Remote Sensing Core Curriculum

The remote sensing core curriculum is an assemblage of content from various authors using various presentation styles. Some of the volumes are reasonably complete, some only provide exercises, and some are not completed. In general this site may provide some useful material for college-level remote sensing educators, but in general the site is not designed for access by the general public.

http://www.r-s-c-c.org/index.html

University of Colorado, Department of Geography – Aerial Photography and Remote Sensing

This presents a brief overview of aerial photography and remote sensing concepts and applications.

http://www.colorado.edu/geography/gcraft/notes/remote/remote_f.html

Canada Centre for Remote Sensing – Learning Resources

The CCRS web site has a broad range of quality remote sensing education resources for remote sensing novices and experts. All of the material is available in English, French, and sometimes other languages. This is likely the most complete set of remote sensing tutorials available on the web.

http://ccrs.nrcan.gc.ca/resource/index_e.php#tutor

Downloading and Formatting Earth Images from Terraserver

This tutorial details how one can download free aerial photography on the Internet and format it for use in remote sensing and GIS software.

http://rockyweb.cr.usgs.gov/public/outreach/terraserver.html

International Institute for Geo-Information Science and Earth Observation (ITC) Remote Sensing Education

This site provides links to a dozen or so different Internet sites that have remote sensing education resources.

http://www.itc.nl/~bakker/education.html

Institute for Advanced Education in Geospatial Sciences (IAEGS)

The IAEGS provides distance learning opportunities for topics in the field of Geospatial Information Technology. The courses are meant to complement conventional classroom learning with the goal being to develop a highly skilled workforce. These courses must be purchased.

http://www.iaegs.com/

A.5.2 Software resources

A.5.2.1 Commercial remote sensing packages

Commercial off the shelf software is designed to visualize and process remotely sensed imagery. These packages all provide a broad range of features necessary when working with remotely sensed imagery. Pricing can be quite variable depending on the type of institution requesting the software and where that institution is located. Price information is not given here. Functionality of the different packages is also not given. Software reviews such as the one on the American Society for Photogrammetry and Remote Sensing web site: (http://www.asprs.org/resources/software/index.html) are available but these software packages constantly undergo improvements so reviews quickly become out of date.

ERDAS IMAGINE

ERDAS IMAGINE, a suite of software products for working with remotely sensed imagery, is the flagship product of Leica Geosystems Geospatial Imaging.

http://gis.leica-geosystems.com

ENVI

ENVI is developed by Research Systems Incorporated (RSI) a subsidiary of ITT Industries. It is developed on the IDL programming language, also developed by RSI.

http://www.rsinc.com

PCI Geomatica

PCI Geomatica is produced by the company PCI Geomatics in Canada. A number of add-on modules are available for advanced processing.

http://www.pcigeomatics.com/

IDRISI Kilimanjaro

IDRISI Kilimanjaro is developed by Clark Labs at Clark University. It runs on low-end Windows computers which makes it appealing to many universities and remote sensing facilities.

http://www.clarklabs.org/

ER Mapper

ER Mapper is the name of the company and the software. The company was recently acquired by Leica Geosystems (the makers of ERDAS), however, it will continue to be sold around the world.

http://www.ermapper.com/

TNTmips

TNTmips is produced by MicroImages. They offer a free version of the software called TNTlite that is fully functional, however, it is limited to working with small images.

http://www.microimages.com/

Image Analyst

Image analyst is Intergraph's desktop image processing and analysis package. It is compatible with their suite of other geospatial offerings.

http://www.intergraph.com/

A.5.2.2 Data translation – Tools for translating data formats:

GDAL
GDAL is a translator library for raster geospatial data formats. A nice implementation of this library can be experienced by using the OpenEV software.
http://www.remotesensing.org/gdal/

WILBER (focus on terrain data)
This software program can import and export many of the popular digital terrain data formats. It does not appear to be actively supported.
http://www.ridgecrest.ca.us/~jslayton/software.html

FME (Feature Manipulation Engine)
FME is a commercial software package that is very popular among GIS and remote sensing practitioners. The software provides capabilities for translating dozens of file formats.
http://www.safe.com/

Geosage
Geosage is an inexpensive Windows program that provides two useful functions: 1) combine image bands into a multi-band image and enhance them and 2) pan-sharpening images by combining a high resolution panchromatic image with a lower resolution multi-spectral image.
http://www.geosage.com/

A.5.2.3 Free data viewers

Free software for viewing remote sensing data:

Data viewers are distributed by commercial companies as a free tool to visualize imagery and in some cases vector data. The capabilities are often a subset of their commercial products. They are often distributed with data products to provide the user with the necessary tools for viewing geo-spatial data. These tools do not qualify as GIS or image processing software.

ArcExplorer
ArcExplorer is distributed by ESRI.
http://www.esri.com/software/arcexplorer/index.html

ER Viewer
ER Viewer is distributed by ER Mapper.
http://www.ermapper.com/downloads/

PCI FreeView
PCI FreeView is distributed by PCI.
http://www.pcigeomatics.com/freeware/freeware.html

ENVI Freelook
ENVI Freelook is distributed by RSI.
http://www.rsinc.com/envi

A.5.2.4 No cost image processing software

OpenEV

OpenEV is an Open Source project to develop a software program that displays and analyses vector and raster geospatial data. It runs on Windows, Linux, and some other Unix platforms, however, a Macintosh port is being discussed. The software is built on various Open Source tools and libraries. The development activity is quite active and many new capabilities are in the works. This is one of the best freely available remote sensing image visualization packages available.

http://openev.sourceforge.net/

NASA Image2000

This is a Java-based image-processing package that was developed by NASA. Currently development has stopped but the program is available for download. The program provides a broad range of functions but is limiting in that it does not handle large datasets well. With additional funding this program has potential.

http://www.ccpo.odu.edu/SEES/ocean/oc_i2k_soft.htm

ImageJ

ImageJ is a Java-based Open Source program that has a good following. The program is being developed by an employee of the National Institutes of Health and the user community. It is a powerful image-processing package geared for the biological and medical sciences. It does not have capabilities for dealing with geospatial data. It claims to be the fastest pure Java image-processing program.

http://rsb.info.nih.gov/ij/

WebWinds

WebWinds is a Java-based data visualization program originally developed at the Jet Propulsion Laboratory and is now being developed by a private organization. Although the interface is not intuitive, it is a powerful visualization tool. It is difficult to say how long this program will be available for free. It has the ability to allow Internet-based distributed processing.

http://www.openchannelfoundation.org/projects/WebWinds/

MultiSpec

MultiSpec is being developed at Purdue University. It is available for the Windows and Macintosh platforms. This software has been embraced by the GLOBE project for a number of their exercises. It was originally designed as a teaching tool but is now used by many remote sensing practitioners. If offers some sophisticated image classification tools.

http://www.ece.purdue.edu/~biehl/MultiSpec/

GRASS

GRASS is an Open Source project originally developed by the United States Corps of Engineers in the early 1980's. GRASS is a powerful raster-based GIS with many image-processing capabilities. It is primarily a command line program designed to run on Windows, Mac OSX, and Linux platforms. GRASS is a bit cumbersome for the first-time user. GRASS is also being integrated into the open source desktop GIS software package Quantum GIS (QGIS – http://qgis.org/).

http://grass.itc.it/index.php

OSSIM

OSSIM stands for the Open Source Software Image Map project. The project leverages existing Open Source algorithms, tools, and packages to construct an integrated tool for remotely sensed image-processing and GIS analysis. The development team recently created a graphical user interface for OSSIM called ImageLinker that runs on all major operating systems. This software has a lot of potential.

http://www.ossim.org/

IDV

IDV stands for Integrated Data Viewer and it is an Open Source Java-based program for visualizing and analysing geoscience data. The program appears to have a focus on weather and atmospheric research, with great 3-D capabilities. Unidata is developing this software.

http://my.unidata.ucar.edu/content/software/metapps/index.html

SPRING

A state-of-the-art GIS and remote sensing image processing system with an object-oriented data model which provides for the integration of raster and vector data representations in a single environment. SPRING is a product of Brazil's National Institute for Space Research. http://www.dpi.inpe.br/spring/

http://www.dpi.inpe.br/spring/english/index.html
http://www.dpi.inpe.br/geopro/trabalhos/spring.pdf

WinDisp (FAO)

WinDisp is focused on early warning and food security issues. It has very basic functionality and limited file importing capabilities. It is being developed by the FAO.

http://www.fao.org/WAICENT/faoinfo/economic/giews/english/windisp/windisp.htm

WinChips

WinChips is a good general purpose Windows-based image processing tool with extensive tools for AVHRR processing. They provide a free "Standard license" but charge for the "Extended license" that provides Orthophoto creation and advanced AVHRR related capabilities. Documentation is good.

http://www.geogr.ku.dk/chips/

ScanMagic Lite

ScanMagicLite provides basic image processing capabilities. The lite version has similar functionallity to the licensed version, however, it does not allow printing and exporting of data.

http://www.scanex.ru/software/scanmagic/default.htm

A.5.2.5 DEM and Terrain (flyby) Visualization tools

Software for use in visualizing Digital Elevation Model (DEM) and terrain data:

MicroDEM

MicroDEM is a Windows program that displays and merges digital elevation models, satellite imagery, and vector data. Professor Peter Guth of the Oceanography Department of the U.S. Naval Academy is currently developing the program.

http://www.nadn.navy.mil/Users/oceano/pguth/website/microdem.htm

The Virtual Terrain Project

The Virtual Terrain Project is an Open Source effort with the goal of creating tools to easily construct any part of the real world in an interactive 3D digital form. The program is designed to run on Windows and Linux computers, with additional development going into a Mac port.

http://www.vterrain.org/

3DEM

This free Windows program will produce 3-D terrain scenes and flyby animations from a wide variety of freely available sources. This is easy to use and it is capable of handling several different data formats. It can also save animations as "*.avi" or "*.mpg" movies.

http://www.visualizationsoftware.com/3dem.html

DG Terrain Viewer

This free Windows program was originally designed to view the SRTM data that NASA distributes for free. A nice GPS data overlay feature was recently added.

http://www.dgadv.com/dgtv

A.5.3 Other Internet resources

General remote sensing information

International Institute for Geo-Information Science and Earth Observation (ITC) Remote Sensing Information

This site offers links to hundreds of sites related to remote sensing. It is a great resource when looking for remote sensing information.

http://www.itc.nl/~bakker/rs.html

Earth Observatory

This is an excellent NASA-sponsored site that publishes easy to read examples of how satellite data are used for a broad variety of applications. There is also a great image archive illustrating several Earth Science concepts. They have an "image of the day" that often depicts some significant natural or anthropogenic event happening around the world.

http://earthobservatory.nasa.gov/

GISUser.com

A GIS-focused site that includes a lot of remote sensing resources including software, data, and articles.

http://www.gisuser.com

SlashGISRS

This is a nice user-driven web site to read about and participate in discussions about GIS and remote sensing happenings.

http://slashgisrs.org

A.5.4. Remote sensing support on the Web

Online resources can be very useful when trying to understand a concept or figure out how to use a particular technique. Simply reading the posted message can help advance one's proficiency in image processing and image interpretation.

In addition to the following sites, most software vendors have online technical support options geared toward their specific software packages.

E-mail list servers

IMAGRS-L

This is an active discussion list that has been around for several years.

http://www.lsoft.com/scripts/wl.exe?SL1=IMAGRS-L&H=CESNET.CZ

GIS List

Although this is a GIS focused list there are occasional remote sensing related questions posted.

http://lists.geocomm.com/mailman/listinfo/gislist

Applied GIS and Remote Sensing List

This list is fairly new but it has become quite popular and has a distinct international flair. It is hosted by a group at the University of Laval in Canada.

http://www.matox.com/agisrs/

The Society for Conversation GIS List

This conservation focused list deals with GIS and remote sensing topics. The participants are friendly and usually quick to respond to questions. To subscribe to this list, visit the Society for Conservation GIS web site (http://www.scgis.org/).

Newsletters

Geo Community

There are three different newsletters available at this site. They all have a GIS focus but occasionally discuss remote sensing issues.

http://spatialnews.geocomm.com/subscribe.html

GIS Monitor

This weekly newsletter provides a good summary of GIS and remote sensing related happenings. It is easy to read and is a good way to keep up with industry developments.

http://www.gismonitor.com

Newsgroups — (these titles are not linked to a URL)

comp.infosystems.gis

This newsgroup is focused on GIS but occasionally discusses remote sensing issues.

sci.image.processing

This is focused on general image processing although there are occasional postings geared toward the remote sensing image processing community.

A.6 Opportunities for operational support

A number of interesting opportunities to share remote sensing data and information currently exist, others are still evolving. Some of these are aimed at facilitating openness within the conservation and Earth science communities. Others are focused on interoperability technologies and data standards. The following section identifies a few such opportunities.

A.6.1 Intergovernmental

The Committee of Earth Observation Satellites (CEOS) (http://www.ceos.org/) is the major international forum for the coordination of Earth observation satellite programs and for the interaction of these programs with users of satellite data worldwide. Any country with Earth observation capabilities is eligible for membership. In addition to its internal activities, CEOS has a substantial outreach activity to developing nations which provides a unique opportunity to interface with the CEOS members. The goals of this outreach effort include:

- assessment of space capabilities versus user requirements;
- data access, ground structures, information services;
- assessment of data use, analysis of lessons from the past;
- promotion of well-designed pilot projects, including user involvement;
- increased education and training;
- growth of local talent;
- provision of infrastructures suited to local operational conditions; and
- improved use of existing user interfaces, with augmentation if necessary.

The intergovernmental Group on Earth Observations (GEO – http://www.earthobservations.org/index.html) is leading a worldwide effort to build a Global Earth Observation System of Systems (GEOSS). GEOSS will work with and build upon existing national, regional, and international systems to provide comprehensive, coordinated Earth observations from thousands of instruments worldwide; transforming the data they collect into vital information for society.

The Food and Agriculture Organization of the United Nations (FAO – http://www.fao.org/) supports a number of programs related to monitoring changes in land cover over time. A number of these are listed below:

- Land Degradation Assessment in Drylands (LADA – http://lada.virtualcentre.org/pagedisplay/display.asp)
- Global Forest Resources Assessment (FRA – http://www.fao.org/forestry/site/fra/en/)
- Global Land Cover Network (GLCN – http://www.glcn-lccs.org/)
- Africover land cover mapping program (http://www.africover.org/)

The Global Biodiversity Information Facility (GBIF) (http://www.gbif.org) members include countries and international organizations who have signed a Memorandum of Understanding that they will share biodiversity data and contribute to the development of increasingly effective mechanisms for making those data available via the Internet. GBIF allows members to share data openly, freely and electronically, so the resource will be dynamic, interactive, and ever-evolving. Within five years, GBIF aims to be the most-used gateway to biodiversity and other biological data on the Internet.

The Conservation Commons (http://www.conservationcommons.org) is a cooperative effort amongst like-minded conservation organizations and research institutions which breaks down barriers to access, more effectively connecting practitioners to data and information assets. It contributes to developing and adopting standards for integrating these assets to support the generation of knowledge and best practice. The purpose of the

Conservation Commons is to ensure open access and fair use of data, information, expertise, and knowledge for the conservation of biodiversity for the benefit of the global conservation community and beyond.

The Inter-American Biodiversity Information Network (IABIN) (http://www.iabin.net/) will provide the networking information infrastructure (such as standards and protocols) and biodiversity information content required by the countries of the Americas to improve decision-making, particularly for issues at the interface of human development and biodiversity conservation. It is developing an Internet-based platform to give access to scientifically credible biodiversity information currently scattered throughout the world in different institutions, such as government organizations, museums, botanical gardens, universities, and NGOs.

The International Organization for Standardization (ISO) (http://iso.org) is the world's largest developer of standards. Although ISO's principal activity is the development of technical standards, ISO standards also have important economic and social repercussions. ISO standards make a positive difference, not just to engineers and manufacturers for whom they solve basic problems in production and distribution, but to society as a whole. ISO standards exist and continue to evolve for geospatial data and information.

The Terrestrial Ecosystem Monitoring Sites (TEMS) (http://www.fao.org/gtos/tems/index.jsp) provide information and access to long-term terrestrial monitoring sites. Over 2000 sites are registered in the TEMS, Terrestrial Ecosystem Monitoring Sites international directory. A substantial amount of information exists at these sites. The goals are outlined as:

- To develop modelling, assessment and research programmes;
- Assess the gaps in geographic coverage of key variables;
- Link ground and satellite observations;
- Evaluate the quality of data and measurement methods;
- Identifying "T.Sites" that need upgrading.

Registration of a site can be done online at: http://www.fao.org/gtos/tems/tsite_edit.jsp

The Global Observation of Forest Cover and Land Dynamics (GOFC-GOLD) (http://www.fao.org/gtos/gofc-gold/) objective is to improve the quality and availability of observations of forests at regional and global scales and to produce useful, timely and validated information products from these data for a wide variety of users. GOFC-GOLD includes a regional network based in Africa, Asia and Eurasia (see http://www.fao.org/gtos/gofc-gold/networks.html for more details).

A.6.2 Non-governmental/non-profit

The Earth Science Information Partnership (ESIP) Federation (http://www.esipfed.org/) is a collaborative between government agencies, universities, non-profit organizations, and businesses in an effort to make Earth Science information available to a broader community. The Federation has been a substantial force for technology and education innovation and for furthering openness, interoperability and the exchange of ideas. Over 3500 data sets are available through the Federation. Note that the Federation is currently composed largely of US interests although many of the participants are actively engaged in and open to international collaborations.

The Open Geospatial Consortium (OGC – http://opengeospatial.org) is a member-driven standards organization which continues to substantively influence the way geographic information systems (GIS) share data. OGC is an international organization and, for those concerned with influencing geospatial standards, membership is worth considering. It should be noted that currently the upper membership levels are largely composed of US government and commercial organizations.

The Open Source Geospatial Foundation (OSGEO – http://www.osgeo.org/) has been created to support and build the highest-quality open source geospatial software. The foundation's goal is to encourage the use and collaborative development of community-led projects.

A.6.3 Other (research, technological initiatives)

Open-source Project for a Network Data Access Protocol (OPeNDAP) (http://opendap.org/index.html) is a technological framework that simplifies all aspects of scientific data networking. It enables users of their software to seamlessly share their data, regardless of original data format. The software may be downloaded from their web site for free. OPeNDAP is an evolving technology but shows great promise for sharing heterogeneous data sources.

The Global Land Cover Facility (GLCF) (http://landcover.org) is a research and applications project dedicated to the free and open distribution of remotely sensed Earth science information. It is associated with the University of Maryland Institute for Advanced Computing Studies. GLCF collaborates in terms of its research, product development and data provision activities. Some collaborators have donated data collections in an effort to further the availability of free data to the science and applications community. GLCF is able to assist CBD members with identifying and meeting remote sensing data requirements (glcf@umiacs.umd.edu).