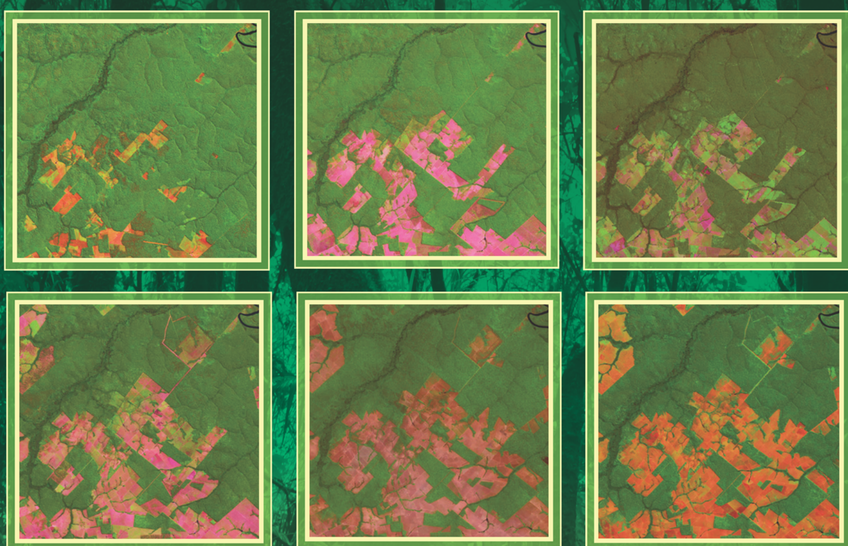
Global Forest Monitoring from Earth Observation

Edited by

Frédéric Achard • Matthew C. Hansen



CRC Press
Taylor & Francis Group

Global Forest Monitoring from Earth Observation

Earth Observation of Global Changes

Series Editor
Chuvieco Emilio

Global Forest Monitoring from Earth Observation
edited by Frédéric Achard and Matthew C. Hansen

Global Forest Monitoring from Earth Observation

Edited by

Frédéric Achard • Matthew C. Hansen

CRC Press
Taylor & Francis Group
Boca Raton London New York

CRC Press is an imprint of the
Taylor & Francis Group, an **informa** business

Joint Research Centre, Institute for Environment and Sustainability

CRC Press
Taylor & Francis Group
6000 Broken Sound Parkway NW, Suite 300
Boca Raton, FL 33487-2742

International Standard Book Number: 978-1-1380-7447-7 (Paperback)
International Standard Book Number: 978-1-4665-5201-2 (Hardback)

Library of Congress Cataloging-in-Publication Data

Global forest monitoring from earth observation / edited by Frederic Achard and Matthew C. Hansen.
p. cm.
Includes bibliographical references and index.
ISBN 978-1-4665-5201-2
1. Forests and forestry--Remote sensing. 2. Forest monitoring. I. Achard, Frédéric. II. Hansen, Matthew C.

SD387.R4G56 2012
333.75--dc23 2012018562

Visit the Taylor & Francis Web site at
http://www.taylorandfrancis.com

and the CRC Press Web site at
http://www.crcpress.com

Contents

Preface

Forest resources are crucial in the context of sustainable development and climate change mitigation. Dynamic information on the location and evolution of forest resources are needed to properly define, implement, and evaluate strategies related to multilateral environmental agreements such as the UN Framework Convention on Climate Change (UNFCCC) and the Convention on Biological Diversity. For the global change scientific community and the UNFCCC process, it is important to tackle the technical issues surrounding the ability to produce accurate and consistent estimates of greenhouse gas emissions and removals from forest area changes worldwide and at the country level.

The following compilation of chapters constitutes a review of why and how researchers currently use remotely sensed data to study forest cover extent and loss over large areas. Remotely sensed data are most valuable where other information, for example, forest inventory data, are not available, or for analyses of large areas for which such data cannot be easily acquired. The ability of a satellite sensor to synoptically measure the land surface from national to global scales provides researchers, governments, civil society, and private industry with an invaluable perspective on the spatial and temporal dynamics of forest cover changes. The reasons for quantifying forest extent and change rates are many. In addition to commercial exploitation and local livelihoods, forests provide key ecosystem services including climate regulation, carbon sequestration, watershed protection, and biodiversity conservation, to name a few. Many of our land use planning decisions are made without full understanding of the value of these services, or of the rate at which they are being lost in the pursuit of more immediate economic gains through direct forest exploitation. Our collection of papers begins with an introduction on the roles of forests in the provision of ecosystem services and the need for monitoring their change over time (Chapters 1 and 2).

We follow this introduction with an overview on the use of Earth observation datasets in support of forest monitoring (Chapters 3 through 5). General methodological differences, including wall-to-wall mapping and sampling approaches, as well as data availability, are discussed. For large-area monitoring applications, the need for systematically acquired low or no cost data cannot be overstated. To date, data policy has been the primary impediment to large-area monitoring, as national to global scale forest monitoring requires large volumes of consistently acquired and processed imagery. Without this, there is no prospect for tracking the changes to this key Earth system resource.

The main section of the book covers forest monitoring using optical data sets (Chapters 6 through 14). Optical datasets, such as Landsat, constitute the longest record of the Earth surface. Our experience of using them in mapping and monitoring forest cover is greater than that of other datasets due to the relatively rich record of optical imagery compared to actively acquired data sets such as radar imagery. The contributions to this section range from indicator mapping at coarse spatial resolution to sample-based assessments and wall-to-wall mapping at medium spatial resolution. The studies presented span scales, environments, and themes. For example, forest degradation, as opposed to stand-replacement disturbance, is analyzed in two chapters. Forest degradation is an important variable regarding biomass, emissions, and ecological integrity, as well as being a technically challenging theme to map. Chapters 6 through 14 also present a number of operational systems, from Brazil's PRODES and DETER products, to Australia's NCAS system. These chapters represent the maturity of methods as evidenced by their incorporation by governments into official environmental assessments. The fourth section covers the use of radar imagery in forest monitoring (Chapter 15). Radar data have a long history of experimental use and are presented here as a viable data source for global forest resource assessment.

We believe that this book is a point of departure for the future advancement of satellite-based monitoring of global forest resources. More and more observing systems are being launched, methods are quickly maturing, and the need for timely and accurate forest change information is increasing. If data policies are progressive, users of all kinds will soon have the opportunity to test and implement forest monitoring methods. Our collective understanding of forest change will improve dramatically. The information gained through these studies will be critical to informing policies that balance the various demands on our forest resources. The transparency provided by Earth observation data sets will, at a minimum, record how well we perform in this task.

We deeply thank Prof. Emilio Chuvieco from the University of Alcalá (Spain) who gave us the opportunity to publish this book and supported and encouraged us in its preparation. We also sincerely thank all the contributors who kindly agreed to take part in this publication and who together have produced a highly valuable book.

Frédéric Achard and Matthew C. Hansen

Editors

Dr. Frédéric Achard is a senior scientist at the Joint Research Centre (JRC), Ispra, Italy. He first worked in optical remote sensing at the Institute for the International Vegetation Map (CNRS/University) in Toulouse, France. Having joined the JRC in 1992, he started research over Southeast Asia in the framework of the TREES (TRopical Ecosystem Environment observations by Satellites) project. His current research interests include the development of Earth observation techniques for global and regional forest monitoring and the assessment of the implications of forest cover changes in the tropics and boreal Eurasia on the global carbon budget. Frédéric Achard received his PhD in tropical ecology and remote sensing from Toulouse University, Toulouse, France, in 1989. He has coauthored over 50 scientific peer-reviewed papers in leading scientific journals including *Nature*, *Science*, *International Journal of Remote Sensing*, *Forest Ecology and Management*, *Global Biogeochemical Cycles*, and *Remote Sensing of Environment*.

Dr. Matthew C. Hansen is a professor in the Department of Geographical Sciences at the University of Maryland, College Park, Maryland. He has a bachelor of electrical engineering degree from Auburn University, Auburn, Alabama. His graduate degrees include a master of engineering in civil engineering and a master of arts in geography from the University of North Carolina at Charlotte and a doctoral degree in geography from the University of Maryland, College Park, Maryland. His research specialization is in large-area land cover monitoring using multispectral, multitemporal, and multiresolution remotely sensed data sets. He is an associate member of the MODIS (Moderate Resolution Imaging Spectroradiometer) Land Science Team and a member of the GOFC-GOLD (Global Observations of Forest Cover and Land Dynamics) Implementation Working Group.

Contributors

Frédéric Achard
Institute for Environment
and Sustainability
Joint Research Centre of
the European Commission
Ispra, Italy

Olivier Arino
Earth Observation Directorate
European Space Agency
Frascati, Italy

Sergey Bartalev
Space Research Institute
Russian Academy of Sciences
Moscow, Russian Federation

Alan Belward
Institute for Environment
and Sustainability
Joint Research Centre of
the European Commission
Ispra, Italy

René Beuchle
Institute for Environment
and Sustainability
Joint Research Centre of
the European Commission
Ispra, Italy

Peter Caccetta
Mathematics, Statistics
and Informatics
Commonwealth Scientific and
Industrial Research Organisation
Floreat, Western Australia,
Australia

Daniel Clewley
Institute of Geography and Earth
Sciences
Aberystwyth University
Aberystwyth, United Kingdom

Rémi D'Annunzio
Forestry Department
Food and Agriculture Organization
of the United Nations
Rome, Italy

Ruth DeFries
Department of Ecology, Evolution
and Environmental Biology
Columbia University
New York, New York

Valdete Duarte
Remote Sensing Division
Brazilian Institute for Space
Research
São Paulo, Brazil

Victor Efremov
Space Research Institute
Russian Academy of Sciences
Moscow, Russian Federation

Vyacheslav Egorov
Space Research Institute
Russian Academy of Sciences
Moscow, Russian Federation

Evgeny Flitman
Space Research Institute
Russian Academy of Sciences
Moscow, Russian Federation

Antonio Roberto Formaggio
Remote Sensing Division
Brazilian Institute for Space Research
São Paulo, Brazil

Suzanne Furby
Mathematics, Statistics and Informatics
Commonwealth Scientific and Industrial Research Organisation
Floreat, Western Australia, Australia

Matthew C. Hansen
Department of Geographical Sciences
University of Maryland
College Park, Maryland

Sean P. Healey
Rocky Mountain Research Station
U.S. Forest Service
Ogden, Utah

Dirk Hoekman
Department of Environmental Sciences, Earth System Science and Climate Change Group
Wageningen University
Wageningen, The Netherlands

Richard A. Houghton
Woods Hole Research Center
Falmouth, Massachusetts

Josef Kellndorfer
Woods Hole Research Center
Falmouth, Massachusetts

Pieter Kempeneers
Earth Observation Department
Flemish Institute for Technological Research
Mol, Belgium

Lars Laestadius
People and Ecosystems Department
World Resources Institute
Washington, DC

Erik Lindquist
Forestry Department
Food and Agriculture Organization of the United Nations
Rome, Italy

Evgeny Loupian
Space Research Institute
Russian Academy of Sciences
Moscow, Russian Federation

Thomas R. Loveland
Earth Resources Observation and Science Center
U.S. Geological Survey
Sioux Falls, South Dakota

Richard Lucas
Institute of Geography and Earth Sciences
Aberystwyth University
Aberystwyth, United Kingdom

Jeffrey G. Masek
NASA Goddard Space Flight Center
Greenbelt, Maryland

Daniel McInerney
Institute for Environment and Sustainability
Joint Research Centre of the European Commission
Ispra, Italy

Humberto Navarro de Mesquita, Jr.
National Forest Registry
Brazilian Forest Service
Brasilia, Brazil

Anssi Pekkarinen
Forestry Department
United Nations Food and Agriculture Organization
Rome, Italy

Peter Potapov
Department of Geographical Sciences
University of Maryland
College Park, Maryland

Gary Richards
Department of Climate Change and Energy Efficiency
Canberra, Australia
and
Fenner School of Environment and Society
Australian National University
Canberra, Australia

Ake Rosenqvist
solo Earth Observation
Tokyo, Japan

Bernardo Friedrich Theodor Rudorff
Remote Sensing Division
Brazilian Institute for Space Research
São Paulo, Brazil

Jesús San-Miguel-Ayanz
Institute for Environment and Sustainability
Joint Research Centre of the European Commission
Ispra, Italy

João Roberto dos Santos
Remote Sensing Division
Brazilian Institute for Space Research
São Paulo, Brazil

Fernando Sedano
Institute for Environment and Sustainability
Joint Research Centre of the European Commission
Ispra, Italy

Lucia Seebach
Department of Forest and Landscape
University of Copenhagen
Copenhagen, Denmark

Yosio Edemir Shimabukuro
Remote Sensing Division
Brazilian Institute for Space Research
São Paulo, Brazil

Masanobu Shimada
Earth Observation Research Center
Japan Aerospace Exploration Agency
Tokyo, Japan

Carlos Souza, Jr.
Amazon Institute of People and the Environment
Belém, Pará, Brazil

Stephen V. Stehman
College of Environmental Science and Forestry
State University of New York
Syracuse, New York

Hans-Jürgen Stibig
Institute for Environment and Sustainability
Joint Research Centre of the European Commission
Ispra, Italy

Peter Strobl
Institute for Environment and Sustainability
Joint Research Centre of the European Commission
Ispra, Italy

Fedor Stytsenko
Space Research Institute
Russian Academy of Sciences
Moscow, Russian Federation

Svetlana Turubanova
Department of Geographical Sciences
University of Maryland
College Park, Maryland

Wayne Walker
Woods Hole Research Center
Falmouth, Massachusetts

Jeremy Wallace
Mathematics, Statistics and Informatics
Commonwealth Scientific and Industrial Research Organisation
Floreat, Western Australia, Australia

Robert Waterworth
Department of Climate Change and Energy Efficiency
Canberra, Australia

Xiaoliang Wu
Mathematics, Statistics and Informatics
Commonwealth Scientific and Industrial Research Organisation
Floreat, Western Australia, Australia

Alexey Yaroshenko
Greenpeace Russia
Moscow, Russian Federation

Ilona Zhuravleva
Greenpeace Russia
Moscow, Russian Federation

1

Why Forest Monitoring Matters for People and the Planet

Ruth DeFries

Columbia University

CONTENTS

1.1 Introduction

In children's tales, forests loom as dark and dangerous places holding mysterious and magical secrets. Hansel and Gretel ventured into the forbidden forest to encounter a child-eating witch. A vicious wolf tricked Little Red Riding Hood when she strayed into the forest. Forests are also places of enchantment, the home of Snow White's seven dwarfs, elves and nymphs, and the castle of the ill-fated prince in *Beauty and the Beast*. The stories revere forests for their magic and revile them for the perils that lurk within.

This dual view of forests persists until today. On the one hand, forests are roadblocks to progress that occupy space more productively used for agriculture. As slash and burn agriculture made its way northward from the Mediterranean coast through Europe, beginning about 4,000 years ago until the first centuries of the common era, forests were replaced by settled agriculture (Mazoyer and Roudart 2006). A similar story played out in North America in the last few centuries, with European expansion preceded by the

Native American's use of fire to manage forests (Williams 2006). Throughout the currently industrialized world, wholesale clearing of forests enabled agriculture to expand and economies to grow. A similar dynamic is currently underway in tropical regions, where economic growth often goes hand-in-hand with agricultural expansion into forested areas (DeFries et al. 2010). There is no doubt that clearing of forests for agriculture played a major role in the expansion of the human species into new areas, the growth in population from 5 million during the dawn of agriculture to over 7 billion today, and increasing prosperity (Mazoyer and Roudart 2006). In this sense, the fairy tale's view of forests as harmful places that are better off cleared resonates with the experience of human history.

The opposite side of the dual view reveres forests for the large range of beneficial services they provide for humanity. Tangible goods such as timber or recreation are apparent. Less apparent are intangible services such as climate regulation, biodiversity, and watershed protection. These regulating ecosystem services are only beginning to be quantified and understood (Millennium Ecosystem Assessment 2005). Without consideration of regulating services from forests, if the economic value of land use following clearing is greater than the economic value of standing forests, the decision to deforest is likely to ensue. This has been the calculus for millennia of forest clearing that has reduced over 40% of the world's forest cover (Figure 1.1).

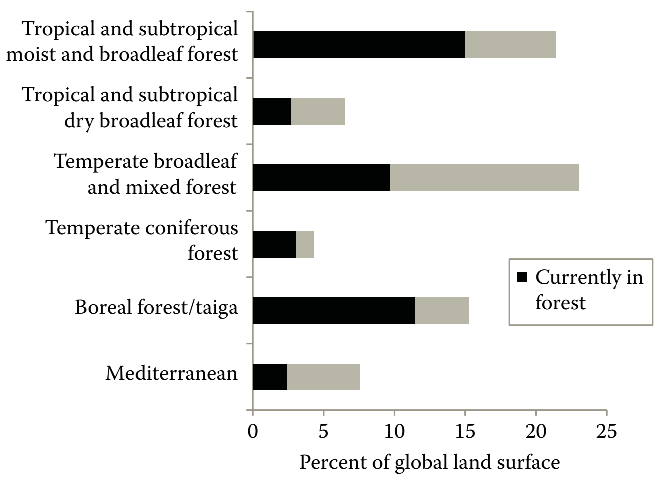


FIGURE 1.1
Approximate percent of the global land surface currently (ca. 1990) occupied by major forests types and the percent previously converted to agriculture. (Values for current percent from Wade, T., et al., *Conserv. Ecol.*, 7, 7, 2003 and values for converted percent derived from Stokstad, E. *Science*, 308, 41, 2005, except for boreal forests which is from Table C2 in Scholes, R., et al. Summary: Ecosystems and their services around the year 2000. In Hassan, R., et al., eds. *Ecosystems and Human Well-Being: Current State and Trends*, vol 1. Washington, DC: Island Press, 2005, 2–23.)

Forest conversion varies greatly in different forest types in different parts of the world. Nearly 70% of Mediterranean forests and almost 60% of temperate deciduous and dry tropical forests have been converted to agriculture. Tropical moist broadleaf forest and boreal forests still have substantial areas of forest remaining.

Remaining forests and the services they provide are increasingly under pressure from both economic and biophysical forces. With increases in population, per capita consumption, and shifts to animal-based diets, demand for agricultural products is estimated to increase by at least 50% by 2050 (Godfray et al. 2010; Nelleman et al. 2009; Royal Society of London 2009). Increasing yield rather than expansion explains the bulk of the vast increase in agricultural production in the last century and is likely to continue to be the main factor in meeting future food demand (Mooney et al. 2005), but agricultural expansion is also likely to continue into the future. Tropical forest and woodlands are the only biomes with substantial area remaining for agricultural expansion. In the past few decades, over 80% of agricultural expansion in the tropics occurred into intact and disturbed forests (Gibbs et al. 2010). Rapid clearing of tropical forests in the last few decades has enabled escalating production of commodities such as oil palm, soy, and sugarcane in response to rising demand (Johnston and Holloway 2007). This pressure on tropical forests and woodlands, particularly in South America and Africa, will only continue in the future with competition of land for food production and biofuels.

Ecological and climatic factors in addition to economic forces are creating pressures on forests. In tropical forests, dry conditions combined with ignition sources create conditions conducive to fires (Chen et al. 2011; van der Werf et al. 2008). In temperate and boreal latitudes, anomalously dry years lead to large forest fires, such as the Russian fires of 2010 (Baltzer et al. 2010). Warmer conditions promote insect outbreaks, such as the pine beetle infestation of western North America, leading to loss of forest stands (Kurz et al. 2008).

These multiple economic, climatic, and ecological forces acting in different parts of the world reverberate to alter the services that forests perform, including habitats that forests provide for other species and the ability of forests to sequester carbon and regulate climate. As both knowledge of the role of forests in providing ecosystem services and the pressures on forests increase, the ability of communities, countries, and global-scale policy makers to monitor forests becomes paramount.

Forests in different parts of the world contribute differentially to ecosystem services, depending on the economic and ecological setting. For example, from an ecological point of view, boreal and peat forests regulate climate through their large stores of belowground carbon while tropical forests contain nearly all of their carbon aboveground. From a socioeconomic point of view, in dry tropical forests with relatively dense populations of poor, forest-dependent people, for example, forests contribute substantially to livelihood needs such as fuel wood and fodder for livestock (Miles et al. 2006). In temperate forests, the recreation value of forests for populations with disposable income for tourism or the need to protect watersheds for large urban centers becomes more important. This heterogeneity in services and pressures on forests create varying needs for monitoring in different parts of the world.

This introductory chapter describes a framework for assessing land use and ecological processes affecting forests and the implications for a range of ecosystem services. The chapter then addresses the evolving needs for forest monitoring in light of information needs to maintain these services.

1.2 Socioeconomic and Ecological Processes Affecting Forests: What Processes Need to Be Monitored?

Methods and approaches to monitor forest extent and condition depend on the processes of interest to the user of the information. These processes—for example, changes in productivity, deforestation, or increases in forest cover—vary greatly in different forest regions around the world and change over time depending on economic and ecological factors. These myriad processes acting on forests require considerable thought in designing monitoring efforts that are flexible and appropriate to the processes occurring in different forest regions.

1.2.1 Land Use Processes

The generalized schematic of land use transitions that accompany economic development provides a framework to view pressures on forests and implications for ecosystem services (DeFries et al. 2004; Mustard et al. 2004). The extent and condition of forests are intricately tied to land use change, as demand for timber, food, and other agricultural products creates pressures to use forests or clear them to make way for croplands and pasture. Pressure to use forested land, in turn, is connected to transitions that typically occur in the course of urbanization, development, and structural transformations in the economy from predominance of agrarian to industrial sectors. Land use typically follows a trajectory from presettlement wildlands with low population densities, to frontier clearing and subsistence agriculture with people reliant on local food production, to higher yield intensive agriculture to support urban populations. Although the details and speed of transitions vary greatly in different places and at different times in history, this general pattern describes the overall trajectory. Different places around the world can be viewed from a lens of their position within this stylized trajectory. On the one hand, the southern Brazilian state of Mato Grosso, for example,

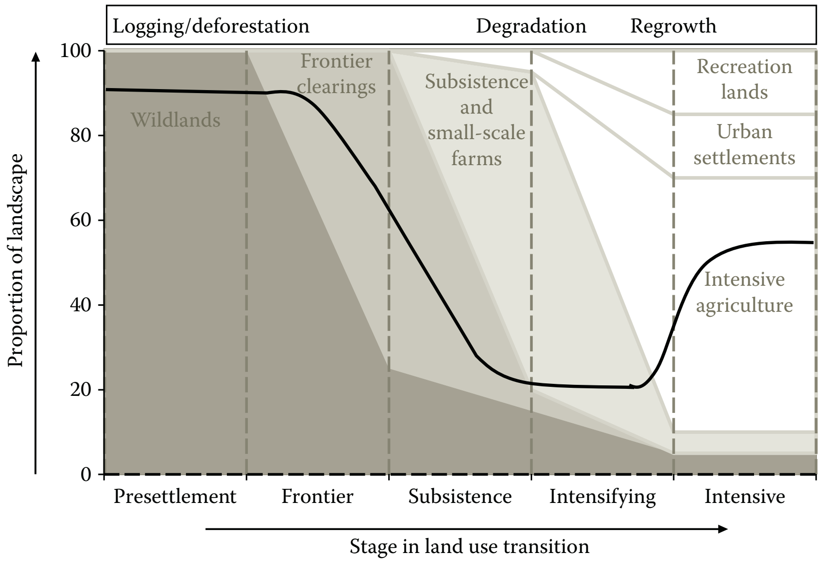


FIGURE 1.2
Generalized land use transition that accompanies economic development, urbanization, and shift from agrarian to industrial economies (DeFries et al. 2004; Mustard et al. 2004). Accompanying proportion of landscape in forest cover (dark line) first declines and then increases with the forest transition (Mather 1992; Rudel et al. 2005; Walker 1993). Proportions of landscape are hypothetical, do not represent actual data, and depict only general patterns that vary in different places. Processes shift from logging and deforestation to degradation and regrowth as regions progress through stages in land use and forest transitions.

is currently undergoing a very rapid transition from wildlands to intensive agriculture, with rapid frontier clearing that largely bypasses the step of subsistence agriculture. South Asia, on the other hand, moved through the frontier clearing of wildlands millennia ago, but much of the land remains in small-scale farming for subsistence and local markets (Figure 1.2).

In forested areas, land use transitions accompany a characteristic trajectory in forest extent and condition. In the early, wildland stage of the land use transition, forests cover extensive areas with low-intensity use for hunting, collection of foods and medicines, or shifting cultivation by low densities of indigenous peoples. With frontier clearing, logging of valuable tree species might occur followed by deforestation and an increasingly fragmented forest. As the transition moves into a period of subsistence agriculture, remaining forest patches are likely to be heavily used for fuel wood, fodder, and nontimber forest product collection. Forest degradation, currently extensive in dry tropical forests of Asia, is the main pressure on forests during a subsistence stage of a land use transition. With urbanization, economic growth, and agricultural intensification, the well-known "forest transition" of increasing forest cover has been observed in many countries (Mather 1992; Rudel et al. 2005; Walker 1993). Rudel et al. (2005) identify two pathways through which increasing forest cover occurs. One pathway is an increase in planted trees incentivized by a shortage of timber; such was the case in Europe. The other pathway is through abandonment of less productive agricultural land as economic growth brings small-scale farmers to urban areas and food production is transported from productive agricultural areas. Such was the case in New England, where forest cover rebounded in areas of abandoned agriculture.

Land use and forest transitions provide a framework to assess monitoring needs in light of the varying pressures on forests at different stages along the transition. Forest areas in distant wildlands are not likely to be undergoing rapid change, consequently requiring less frequent monitoring for human impacts. In frontier forests undergoing a transition from wildlands, deforestation and degradation from unsustainable logging are the activities requiring monitoring. Places in a mode of small-scale farming with local reliance on forest patches for livelihood needs are subject to degradation. Monitoring for deforestation in such locations is less relevant and degradation is more likely to be important. Finally, in the later stages of a land use transition, regrowth of forests becomes an important process, requiring a monitoring strategy to identify increases rather than decreases of tree cover.

As different places move through land use and forest transitions, the processes that require monitoring will shift. Monitoring efforts for deforestation might most usefully focus on frontier regions and monitoring for degradation in postfrontier remaining forest patches. Monitoring to identify regrowth is most relevant in those places undergoing agricultural abandonment. Methods vary to monitor these different processes, requiring flexibility in monitoring efforts as processes requiring monitoring change.

1.2.2 Ecological Processes

As with land use processes, ecological processes affecting forests vary in different places. The types of ecological processes that may be important for monitoring systems to identify include:

Biome shifts in response to climate change: Climate change is already leading to shifts in boundaries of forests biomes in high latitudes (Beck et al. 2011). In the tropics, a biome shift between savanna and forest has been hypothesized with a drier climate and increased fires (Hirota et al. 2010). As the process of biome shifts is heterogeneous and conflicting evidence arises from different places, a remote sensing approach is critical to enable observations over large areas. Shifts in forest boundaries have major consequences for carbon storage and biophysical feedbacks to climate through changes in albedo and evapotranspiration of the land surface. A long-term monitoring system that enables observations of changes in forest boundaries allows earth system models to incorporate dynamic interactions between vegetation and climate in the growing field of dynamic vegetation models (Gonzalez et al. 2010). The ability to monitor such changes over large areas at fine spatial resolution is becoming more feasible.

Changes in forest ecosystems in response to atmospheric chemistry: Enhanced forest productivity and biomass accumulation attributable to fertilization from elevated carbon dioxide concentrations is controversial but may explain increased productivity and biomass accumulation in tropical forests (Lewis et al. 2009). Nitrogen deposition is another forcing factor on forest productivity, with studies suggesting an effect on species composition and ecosystem function in temperate and northern Europe and North America (Bobbink et al. 2010). Long-term monitoring of productivity cannot attribute the cause of any observed changes, but is a critical piece to unraveling the responses of forests to changing atmospheric chemistry.

Fire: The ability to monitor active fires (Justice et al. 2002) and burned areas (Giglio et al. 2010) with remote sensing has developed rapidly. Many types of fires affect forests, including intentionally set deforestation fires, fires escaped from land management, and fires ignited by lightning. The extent to which these fires occur depends on multiple factors such as climate, fuel loads, and ignition sources. Fire is a particularly complex phenomenon that combines climatic, ecological, and human factors (Bowman et al. 2009).

A framework to identify monitoring needs through a lens of economic and ecological processes creates the need for multiple approaches that can vary through space and time. To date, global monitoring with remote sensing has focused predominantly on forest extent. As methods develop, robust global forest monitoring in the longer term should assess changes occurring in response to the full suite of processes affecting forests throughout the world.

1.3 Ecosystem Services from Forests

Monitoring systems aim to identify changes in the extent and condition of forests so that timely and effective policies can be put in place to avoid negative consequences for ecosystem services. Forests provide many ecosystem services that accrue benefits at proximal, downstream, and distal scales. Similar to the processes affecting forests discussed above, ecosystem services from forests and their beneficiaries vary across forest regions according to socioeconomic and ecological settings. Consequently, monitoring methods and approaches need to vary depending on the ecosystem services of concern. A monitoring system that aims to be applied to the implementation of

TABLE 1.1

Some Ecosystem Services Accruing to Beneficiaries at Different Spatial Scales from Forests in Varying Stages of Land Use Transitions

Location of Beneficiary	Forest Condition by Stage of Land Use Transition		
	Wildlands Prior to Frontier Clearing	*Forest Fragments Embedded in Small-Scale Agricultural Land*	*Regrowth with Agricultural Intensification*
Proximate	Livelihood needs and local regulating services (e.g., pollination) for low density of forest-dependent people	**Livelihood needs and local regulating services for high density of forest-dependent people**	
Downstream		Prevention of soil erosion, flood regulation, water purification	**Prevention of soil erosion, flood regulation, water purification**
Distal	**Carbon storage, biodiversity**	Biodiversity in forest fragments	Carbon sequestration, biodiversity in secondary forest

Note: Dominant ecosystem service of each stage based on author's judgment is in bold.

REDD (reducing emissions from deforestation and degradation), for example, requires observations of forest extent and biomass while a system aimed at biodiversity requires monitoring of habitat and forest structure. The following highlights the range of ecosystem services from forests at different scales (Table 1.1).

Proximal: Ecosystem services from forests play a particularly essential role for forest-dependent people throughout the global South (Agrawal et al. 2011). Natural capital from forests is a disproportionately large component for millions of poor households and communities relying directly on forests for livelihood needs. Services from forests include fuel wood, fodder for livestock, nontimber forest products to generate income, meat for protein, and medicinal plants. On the one hand, regulating services such as clean water, pollination, disease regulation, and pest control as well as spiritual and cultural importance of forests are more difficult to quantify but are important locally. On the other hand, forests and, particularly, protected areas harbor species that provide a disservice to local communities by crop raiding and livestock predation affecting local residents (White and Ward 2010) and spread of zoonotic diseases (Keesing et al. 2010).

Downstream: The watershed protection value of forests has garnered the most tractable implementation of payment for ecosystem service schemes. Forests buffer runoff to regulate floods and filter water to improve water quality.

Well-known examples of forest conservation for watershed protection include watersheds for the surface water supply of urban areas such as New York City and Quito, Ecuador (Postel and Thompson 2005). In addition to downstream users, another example of the role of forests at a regional scale is through energy balance and evapotranspiration, such as the Amazon basin where deforestation leads to decreases in basin-wide precipitation of climate and downwind transport of vapor (Davidson et al. 2012).

Distal: Global-scale services from forests accrue to beneficiaries living far away. Carbon storage to maintain carbon in vegetation rather than as a greenhouse gas in the atmosphere is a critical role for forests. Terrestrial vegetation and litter combined contain approximately the same amount of carbon as the atmosphere (850 and 780 Pg, respectively), with forests a particularly important reservoir for carbon (Houghton 2007). Tropical forests are exceptionally valuable for biodiversity in terms of species richness, family richness, and species endemism (Mace et al. 2005). Distal beneficiaries of biodiversity value the knowledge of existence as well as the functional role of biodiversity for disease regulation, resilience to disturbance, and other functions (Thompson et al. 2011).

In sum, forests provide a myriad of ecosystem services that vary in different forest regions. Aboveground carbon storage and biodiversity are particularly relevant in humid tropical forests. Local livelihood needs are relevant in dry tropical forests, and watershed protection is particularly relevant in forests upstream of urban centers reliant on surface water. Communities, national governments, and global policy makers place varying priorities on different ecosystem services. For example, local communities may place little value on carbon and biodiversity services that accrue to distal beneficiaries, while global policy makers may place little value on forest products and other livelihood needs for local communities. This mismatch in scales and differences in priorities about which ecosystem services are most important create tensions for designing monitoring systems.

The importance of different ecosystem services may vary through time as places move through land use transitions. Monitoring systems designed to address particular ecosystem services might require flexibility as priorities shift. For example, if carbon storage is the rationale for a monitoring program, the focus might be on frontier regions aimed at reducing deforestation and on late-stage transitions aimed at sequestering carbon through regrowth (Lambin and Meyfroidt 2011). If the rationale were rather on local livelihood needs for forest products, a monitoring system would focus on places in a subsistence stage of the land use transition to monitor degradation. For watershed protection, riparian forest cover would be of primary importance.

In reality, existing monitoring systems have not explicitly identified the rationale in terms of ecosystem services. Monitoring systems ideally would be relevant for multiple ecosystem services to make effective use of the investment. As monitoring systems are implemented in different countries throughout the developing world in different stages of land use transitions, explicit consideration of the ecosystem services of interest may be a useful undertaking.

1.4 Evolving Capabilities for Forest Monitoring

Forest monitoring to date (FAO 2010; Forest Survey of India 2005; INPE 2007) has mainly focused on the areal extent of forest cover and changes over time. Other variables of forest condition are increasingly becoming possible to monitor from satellites. Biomass, a key variable for carbon storage, has traditionally been collected through ground-based inventories. Recent abilities to assess biomass using remote sensing (Saatchi et al. 2006) are promising technological advances that are becoming more amenable to operational implementation. Monitoring degradation from logging with the spatial pattern characteristic of the Amazon has also advanced to be operational (Asner et al. 2006; Souza Jr. et al. 2005). These advances represent major progress for subnational, national, and global efforts to monitor forests and the ecosystem services they provide.

While these advances are major achievements, several aspects of forest condition are still in need of methodological development to address the full range of ecosystem services and socioeconomic and ecological processes affecting forests in different parts of the world. One such need is forest degradation related to local uses such as fuel wood collection and forest grazing, such as occurring extensively in Asian forests with high density of poor populations dependent on local ecosystem services. While monitoring of degradation characteristics of logging in the Amazon has advanced, monitoring of degradation from other local uses has not progressed to the same degree. Another aspect that has not been incorporated in monitoring is postclearing land use. The land use and management following deforestation, such as fertilizer use, agricultural activity, and crop type and diversity, has implications for ecosystem services and is required information to assess the impact of deforestation (Galford et al. 2010). While methods have advanced to assess postclearing land use in terms of pasture versus crop (Macedo et al. 2012), other aspects of land management require attention. Finally, the importance of lands outside forests for ecosystem services such as biodiversity, so-called land sharing, is evident, given the inability to protect enough lands to preserve all biodiversity. India's national monitoring efforts to assess trees outside forests (Forest Survey of India 2005) is a step toward addressing this need. Additional forest variables including vegetation structure and connectivity are integral yet unrealized aspects of monitoring to maintain ecosystem services.

1.5 Conclusion

Interest and investments in forest monitoring systems have risen sharply, mainly in anticipation of REDD. Monitoring systems at global, national, subnational, and community levels are all components of the interest in establishing monitoring systems. As these investments move forward, it is timely to consider the purposes of a monitoring system in terms of which land use-driven and ecological processes need to be captured and how the information can be used to track changes in ecosystem services.

Forests in different parts of the world are facing pressures from both economic and biophysical factors. For instance, tropical forests are under pressure from economic forces for agricultural expansion, while forests in high latitudes are moving northward due to climate change. Land use and forest transition frameworks provide a context to identify the processes affecting forests in varying paths along a development trajectory, with deforestation and degradation altering forests in early stages and regrowth in later stages with agricultural intensification and urbanization. From a biophysical point of view, ecological processes related to biome shifts from climate change, enhanced productivity from changing atmospheric chemistry, and fire are altering forest extent and biomass. Monitoring approaches vary depending on which processes are of interest. For example, a monitoring system to track human land use change would most effectively focus on frontier regions and less on wildlands. If the process of interest is productivity change, a comprehensive monitoring of biomass in wildlands is needed.

Approaches for monitoring systems also vary depending on which ecosystem services are of interest to the user. Forests provide a multitude of ecosystem services at a range of scales. Some services accrue benefits at proximal (e.g., forest products for local livelihoods), some downstream (e.g., watershed protection), and some at distal scales (e.g., carbon storage and biodiversity). Perspectives on which ecosystem services are most important depend on the user. Local communities are likely to place more importance on those ecosystem services of value to their needs while global policy makers are likely to place importance on global-scale, distal services.

Traditionally, forest monitoring and inventories have been designed around the commercial value of forests. With increasing emphasis on the value of forests for carbon storage, conservation of biodiversity, watershed protection, and a myriad of other ecosystem services, the focus for monitoring systems becomes more complex. Explicit consideration of the ecosystem services of interest and the methods required to monitor changes in those services require attention to design systems that are relevant for a country's circumstances. Advancements in technologies that enable monitoring of biomass, postclearing land use, forest structure, and other attributes are rapidly developing and offer a wide menu of possibilities for monitoring systems.

About the Contributor

Ruth DeFries is Denning Professor of Sustainable Development in the Department of Ecology, Evolution, and Environmental Biology at Columbia University, New York. Her research uses remote sensing and field data to analyze patterns of land use change and consequences for climate regulation, biodiversity, and other ecosystem services. A particular focus is tropical landscapes and the trade-offs and synergies between agricultural production and maintenance of ecosystem services and human well-being.

References

Agrawal A, Nepstad DC, and Chhatre A, Reducing emissions from deforestation and forest degradation. *Annual Review of Environment and Resources*, 36, 2011, 373–396.

Asner GP, Broadbent EN, Oliviera P, Keller M, Knapp DE, and Silva JNM, Condition and fate of logged forests in the Brazilian Amazon. *Proceedings of the National Academy of Sciences*, 103(34), 2006, 12947–12950.

Baltzer H, Tansey K, Kaduk J, George C, Gerard F, Gonzales MC, Sukhinin A, and Ponomarev E, Fire/climate interactions in Siberia. in Baltzer H, ed. *Environmental Change in Siberia: Earth Observation, Field Studies and Modelling*, vol. 40, *Advances in Global Change Research*. Dordrecht, The Netherlands: Springer, 2010, 21–36.

Beck P, Juday G, Alix C, Barber V, Winslow S, Sousa E, Heiser P, Herriges J, and Goetz S, Changes in forest productivity across Alaska consistent with biome shift. *Ecology Letters*, 14, 2011, 373–379.

Bobbink R, et al., Global assessment of nitrogen deposition effects on terrestrial plant diversity: A synthesis. *Ecological Applications*, 20(1), 2010, 30–59.

Bowman D, et al., Fire in the earth system. *Science*, 324, 2009, 481–484.

Chen Y, Randerson J, Morton D, DeFries R, Collatz GJ, Kasibhatla P, Giglio L, Jin Y, and Marlier M, Fire season severity in South America using sea surface temperature anomalies. *Science*, 334(6057), 2011, 787–791.

Davidson E, et al., The Amazon basin in transition. *Nature*, 481, 2012, 321–328.

DeFries R, Asner GP, and Houghton RA, Trade-offs in land-use decisions: Towards a framework for assessing multiple ecosystem responses to land use change. in DeFries R, Asner GP, and Houghton RA, eds. *Ecosystems and Land Use Change*, vol. 153. Washington, DC: American Geophysical Union, 2004, 1–12.

DeFries R, Rudel TK, Uriarte M, and Hansen M, Deforestation driven by urban population growth and agricultural trade in the twenty-first century. *Nature Geoscience*, 3, 2010, 178–181.

FAO, *Global Forest Resources Assessment 2010: Main Report*. Rome, Italy: Food and Agriculture Organization. 2010.

Forest Survey of India, *State of Forest Report 2005*. Dehradun, India: Ministry of Environment and Forests. 2005.

Galford GL, Melillo J, Kicklighter D, Cronin T, Cerri CEP, Mustard J, and Cerri CC, Estimating greenhouse gas emissions from land-cover and land-use change: Future scenarios of deforestation and agricultural management. *Proceedings of the National Academy of Sciences*, 107, 46, 2010.

Gibbs HK, Ruesch AS, Achard F, Clayton MK, Holmgren P, Ramankutty N, and Foley J, Tropical forests were the primary sources of new agricultural land in the 1980s and 1990s. *Proceedings of the National Academy of Sciences*, 107(38), 2010, 16732–16733.

Giglio L, Randerson JT, Van der Werf G, Kasibhatla P, Collatz GJ, Morton D, and DeFries R, Assessing variability and long-term trends in burned area by merging multiple satellite fire products. *Biogeosciences Discussion*, 7, 2010, 1171–1186.

Godfray H, Beddington J, Crute I, Haddad L, Lawrence D, Muir J, Pretty J, Robison S, Thomas S, and Toulmin C, Food security: The challenge of feeding 9 billion people. *Science*, 327, 2010, 812–818.

Gonzalez P, Neilson R, Lenihan J, and Drapek R, Global patterns in the vulnerability of ecosystems to vegetation shifts due to climate change. *Global Ecology and Biogeography*, 19, 2010, 755–768.

Hirota M, Nobre CA, Oyama M, and Bustamante M, The climatic sensitivity of the forest, savanna and forest-savanna transition in tropical South America. *New Phytologist*, 187(3), 2010, 707–719.

Houghton RA, Balancing the global carbon budget. *Annual Review of Earth and Planetary Sciences*, 35, 2007, 313–347.

INPE, PRODES DIGITAL. (December 30, 2006 http://www.obt.inpe.br/prodes/prodes_1988_2007.htm), 2007.

Johnston M and Holloway T, A global comparison of national biodiesel production potentials. *Environmental Science and Technology*, 41(23), 2007, 7967–7973.

Justice CO, Giglio L, Korontzi S, Owens J, Morisette J, Roy D, Descloitres J, Alleaume S, Petitcolin F, and Kaufman Y, The MODIS fire products. *Remote Sensing of Environment*, 83(1–2), 2002, 244–262.

Keesing F, et al., Impacts of biodiversity on the emergence on transmission of infectious disease. *Nature*, 468, 2010, 647–652.

Kurz WA, Dymond CC, Stinson G, Rampley GJ, Neilson ET, Carroll AL, Ebata T, and Safranyik L, Mountain pine beetle and forest carbon feedback to climate change. *Nature*, 452, 2008, 987–990.

Lambin E and Meyfroidt P, Global land use change, economic globalization, and the looming land scarcity. *Proceedings of the National Academy of Sciences*, 108(9), 2011, 3465–3472.

Lewis S, Lloyd J, Sitch S, Mitchard E, and Laurance W, Changing ecology of tropical forests: Evidence and drivers. *Annual Review of Ecology, Evolution, and Systematics*, 40, 2009, 529–549.

Mace G, Masundire H, and Baillie J, Biodiversity. in Hassan R, Scholes R, and Ash N, eds. *Millennium Ecosystem Assessment Working Group on Conditions and Trends*, vol 1. Washington, DC: Island Press, 2005.

Macedo M, DeFries R, Morton D, Stickler C, Galford G, and Shimabukuro Y, Decoupling of deforestation and soy production in the southern Amazon during the late 2000s. *Proceedings of the National Academy of Sciences*, 109(4), 2012, 1841–1846.

Mather AS, The forest transition. *Area*, 24, 1992, 367–379.

Mazoyer M and Roudart L, *A History of World Agriculture: From the Neolithic Age to the Current Crisis*. New York: Monthly Review Press, 2006.

Miles L, Newton AC, DeFries R, Ravilious C, May I, Blyth S, Kapos V, and Gordon J, A global overview of the conservation status of tropical dry forests. *Journal of Biogeography*, 33, 2006, 491–505.

Millennium Ecosystem Assessment, *Ecosystems and Human Well-Being: Synthesis*. Washington, DC: Island Press, 2005.

Mooney HA, Cropper A, and Reid WV, Confronting the human dilemma: How can ecosystems provide sustainable services to benefit society? *Nature*, 434, 2005, 561–562.

Mustard J, DeFries R, Fisher T, and Moran EF, Land use and land cover change pathways and impacts. in Gutman G, Janetos J, Justice CO, Moran EF, Mustard J, Rindfuss R, Skole DL, Turner BL, and Cochrane MA, eds. *Land Change Science: Observing, Monitoring, and Understanding Trajectories of Change on the Earth's Surface*. Dordrecht, The Netherlands: Springer, 2004.

Nelleman C, MacDevette M, Manders T, Eickhout B, Svihus B, Prins A, and Kaltenborn B, *The Environmental Food Crisis: The Environment's Role in Averting Future Food Crises*. GRID-Arendal: United Nations Environment Program. 2009.

Postel S and Thompson B, Watershed protection: Capturing the benefits of nature's water supply services. *Natural Resources Forum*, 29, 2005, 98–108.

Royal Society of London, *Reaping the Benefits: Science and the Sustainable Intensification of Global Agriculture*. London: Royal Society of London. 2009.

Rudel TK, Coomes OT, Moran EF, Achard F, Angelsen A, Xu J, and Lambin E, Forest transitions: Towards a global understanding of land use change. *Global Environmental Change*, 15, 2005, 23–31.

Saatchi S, Houghton RA, Alvala RC, Soares J, and Yu Y, Distribution of aboveground live biomass in the Amazon Basin. *Global Change Biology*, 13(4), 2006, 816–837.

Scholes R, Hassan R, and Ash N, Summary: Ecosystems and their services around the year 2000. in Hassan R, Scholes R, and Ash N, eds. *Ecosystems and Human Well-Being: Current State and Trends*, vol 1. Washington, DC: Island Press, 2005, 2–23.

Souza Jr. CM, Roberts D, and Cochrane MA, Combining spectral and spatial information to map canopy damages from selective logging and forest fires. *Remote Sensing of Environment*, 98, 2005, 329–343.

Stokstad E, Taking the pulse of the Earth's life-support systems. *Science*, 308, 2005, 41–43.

Thompson I, Okabe K, Tylianakis J, Kumar P, Brockerhoff E, Schellhorn N, Pattotta J, and Nasi R, Forest biodiversity and the delivery of ecosystem goods and services: Translating science into policy. *BioScience*, 61(12), 2011, 972–981.

van der Werf GR, et al., Climate regulation of fire emissions and deforestation in equatorial Asia. *Proceedings of the National Academy of Sciences*, 105(51), 2008, 20350–20355.

Wade T, Riitters K, Wickham J, and Jones KB, Distribution and causes of global forest fragmentation. *Conservation Ecology*, 7(2), 2003, 7.

Walker R, Deforestation and economic development. *Canadian Journal of Regional Science*, 16(3), 1993, 481–497.

White P and Ward A, Interdisciplinary approaches for the management of existing and emerging human-wildlife conflicts. *Wildlife Research*, 37(8), 2010, 623–629.

Williams M, *Deforesting the Earth: From Prehistory to Global Crisis*. Chicago, IL: The University of Chicago Press, 2006.

2

Role of Forests and Impact of Deforestation in the Global Carbon Cycle

Richard A. Houghton
Woods Hole Research Center

CONTENTS

2.1 Introduction

Forests are important in the global carbon cycle because they hold in their vegetation and soils about as much carbon as is held in the atmosphere (Table 2.1), and, with an annual GPP of 65 PgC yr^{-1} (Beer et al. 2010), forests circulate about 8% of the atmosphere's carbon each year through photosynthesis and respiration. These exchanges are part of the natural carbon cycle. More important from the perspective of climate change is the role that forests play in altering the concentration of atmospheric CO_2 over decades to centuries. This chapter discusses forests in that role. It begins with a brief review of the global carbon cycle and goes on to discuss, first, the global carbon sink measured in forest inventories, second, sources and sinks of carbon that result from direct human use of forests, and, third, possible

TABLE 2.1

Stocks and Flows of Carbon

Carbon Stocks (PgC)	(Forests)
Atmosphere	825
Land	2,000
Vegetation	500 (436)
Soil	1,500 (426)
Ocean	39,000
Surface	700
Deep	38,000
Fossil fuel reserves	10,000
Annual Flows (PgC yr^{-1})	
Atmosphere–oceans	90
Atmosphere–land	120 (65)
Net Annual Exchanges (PgC yr^{-1} Averaged over 2000–2009)	
Fossil fuels	7.7
Land use change	1.1 (1.0)
Atmospheric increase	4.1
Oceanic uptake	2.3
Residual terrestrial sink	2.4 (2.4)

reasons why the results from inventories and analyses of land use change do not agree. The chapter ends with a discussion of the processes affecting carbon storage on land that are and are not amenable to monitoring with satellites.

Note that forests affect climate through emissions of chemically and radiatively active gases other than CO_2, including other carbon compounds. Further, changes in forest area affect climate biogeophysically as well as biogeochemically through effects on albedo, surface roughness, and evapotranspiration (e.g., Pongratz et al. 2010). Non-CO_2 gases and biophysical effects are not considered here.

2.2 Global Carbon Cycle

The global carbon cycle is the exchange of carbon between the four major reservoirs: atmosphere, oceans, land, and fossil fuels. This chapter, and most of carbon cycle science, is concerned with anthropogenic carbon, that is, the amount of carbon emitted each year from combustion of fossil fuels and land use change and the sinks for that carbon in the atmosphere, oceans, and land. Forests play a major role in both the emissions of carbon from land use change and the sinks of carbon on land.

Figure 2.1 shows the annual sources and sinks of carbon in the major global reservoirs over the last century and a half. The most noticeable

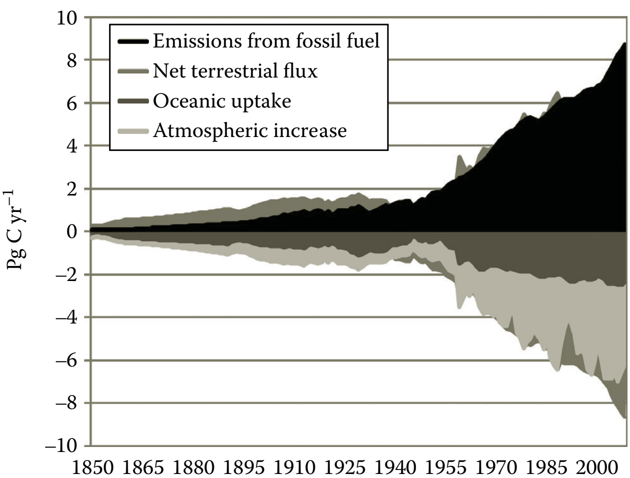


FIGURE 2.1
Annual sources (+) and sinks (–) in the global carbon budget. Note that the net terrestrial flux was consistently a net source before 1940, but has been a variable and growing sink in recent decades.

TABLE 2.2

Global Carbon Budget

	1980s	1990s	2000–2009
Fossil fuel emissions	5.5 ± 0.3	6.4 ± 0.4	7.7 ± 0.5
Land use change	1.5 ± 0.7	1.6 ± 0.7	1.1 ± 0.7
Atmospheric increase	–3.4 ± 0.1	–3.1 ± 0.2	–4.1 ± 0.1
Oceanic uptake	–2.0 ± 0.6	–2.2 ± 0.7	–2.3 ± 0.4
Residual terrestrial sink	–1.6 ± 1.0	–2.7 ± 1.0	–2.4 ± 1.0

Source: From Le Quéré, C., et al., *Nature GeoSci.*, 2, 831, 2009 and http://www.globalcarbonproject.org/carbonbudget/09/files/GCP2010_CarbonBudget2009.pdf.

Notes: Units are PgC yr^{-1}. Positive values indicate sources of carbon to the atmosphere; negative values indicate sinks, or removals from the atmosphere.

feature of the history is the increasing rate at which carbon has been emitted from combustion of fossil fuels (including cement production and gas flaring). In recent decades, the emissions have grown from 5.5 PgC yr^{-1} averaged for the 1980s to 6.4 PgC yr^{-1} for the 1990s to 7.7 PgC yr^{-1} over the period 2000–2009 (Table 2.2). After a slump in 2009 from the global financial crisis, fossil fuel emissions were above 9 PgC in 2010 (Peters et al. 2012). The annual emissions from fossil fuels are calculated from reports from the United National Energy Statistics. The error is thought to be ±6% (Le Quéré et al. 2009).

The figure also reveals that the sinks for carbon in the atmosphere, land, and oceans have increased over time, in proportion to annual emissions. In 1958 the average concentration of CO_2 in air at Mauna Loa was about 315 ppm; in 2010 it was about 390 ppm. Today there are nearly 200 stations, worldwide, where weekly flask samples of air are collected, analyzed for CO_2 and other constituents, and where the resulting data are integrated into a consistent global data set (http://www.esrl.noaa.gov/gmd/ccgg/). The rate of increase in concentrations averaged about 1 ppm yr^{-1} in the 1950s and 1960s, about 1.5 ppm yr^{-1} in the 1980s and 1990s, and about 1.9 ppm yr^{-1} between 2000 and 2009. The increase of 1.9 ppm CO_2 yr^{-1} is equivalent to an increase of ~4 PgC yr^{-1}. The error is 0.04 PgC yr^{-1} (Canadell et al. 2007).

The annual uptake of carbon by the world's oceans is based on ocean general circulation models coupled to ocean biogeochemistry models (Le Quéré et al. 2009), corrected to agree with the observed uptake rates over 1990–2000 (Canadell et al. 2007). The error in the modeled oceanic sink is thought to be 0.4 PgC yr^{-1}.

There are no direct measurements of terrestrial sources or sinks globally. Instead, the annual net exchange of carbon between land and the atmosphere is calculated by the difference between the annual release of carbon from fossil fuels and the annual accumulations in the atmosphere and oceans. The total emissions must balance the total sinks. The net terrestrial flux of carbon was a small source before 1940 and a sink after. That sink is variable year to year and appears to have grown in recent decades. It averaged 1.3 PgC yr^{-1} between 2000 and 2009. The role of forests in the historic source of carbon and the more recent sink is the topic of this chapter.

2.3 Forest Inventories

A recent paper by Pan et al. (2011) summarized the results of measurements obtained through forest inventories. Countries in temperate zone and boreal regions have systematic forest inventories that periodically measure the volumes of timber. Biomass and carbon densities can be calculated from these measurements of wood volume. The inventories often include measurement of belowground carbon stocks and coarse woody debris on the forest floor, and estimates are also made of the storage of carbon in wood products and land fills. Because nearly all forests are sampled in these inventories, the change in carbon storage from one inventory to another represents the total change in forest carbon, including wood products—a net sink in temperate and boreal forests of 1.22 PgC yr^{-1} averaged over the period 2000–2007 (Table 2.3).

This measured sink is a net sink composed of both releases of carbon from fire, storms, disease, and logging and uptake of carbon in growing forests. It is worth noting that the sampling used to obtain these estimates is arguably better for measuring changes in wood volume in existing forests than it is for measuring changes in forest area. A satellite-based approach might provide more accurate estimates of changes in forest area.

The net sink for the world's temperate zone and boreal forests does not mean that all such forests were sinks. Canadian forests, for example, were a small source over 1990–2007, and European forests were a net source over 2000–2007, according to analyses of forest inventories (Pan et al. 2011). Furthermore, studies based on analyses of satellite data suggest that forest area has been declining, for example, in the eastern United States (Drummond and Loveland 2010; Jeon et al. 2011).

Systematic inventories of forests are rare in tropical countries. However, small permanent plots (generally ~1 ha) have been inventoried for years in the unmanaged, or intact, forests of Amazonia (Phillips et al. 2004, 2008) and Africa (Lewis et al. 2009). These inventories show an average net accumulation of 0.84 MgC/ha yr^{-1} in biomass. The total area of tropical forests in 2010 was 1949 million ha (FAO 2010), but the area of intact

TABLE 2.3

Average Annual Net Source (+) or Sink (–) for Carbon Based on (A) Forest Inventories and (B) LULCC

	1980s	1990s	2000–2007
A. Forest Inventories			
Temperate and boreal forests (a)	–1.17 ± 0.11	–1.28 ± 0.12	–1.22 ± 0.11
Intact tropical forests (b)	–1.33 ± 0.35	–1.02 ± 0.47	–1.19 ± 0.41
Total	–2.50	–2.30	–2.41
B. LULCC			
Temperate and boreal forests			
Gross uptake (c)	–1.38	–1.48	–1.56
Gross emissions	1.51	1.53	1.52
Net flux	0.13	0.05	–0.04
Tropical forests			
Gross uptake (d)	–1.57 ± 0.50	–1.72 ± 0.54	–1.64 ± 0.52
Gross emissions	3.03 ± 0.49	2.82 ± 0.45	2.94 ± 0.47
Net tropical LULCC flux (e)	1.46 ± 0.70	1.10 ± 0.70	1.30 ± 0.70
Net flux for tropical forest (b + e)	0.13	0.08	0.11
Net global forest sink (a + b + e)	–1.04 ± 0.79	–1.20 ± 0.85	–1.11 ± 0.82
Gross global forest sink[a] (a + b + d)	–4.07	–4.02	–4.05
Gross global forest sink[b] (a + b + c + d)	–5.45	–5.50	–5.61

Source: From Pan, Y., et al., *Science* 333, 988, 2011.

[a] As reported by Pan et al. (2011).

[b] With gross uptake in temperate and boreal forests (c) included.

forests, for which this average accumulation applies, was smaller. At least 557 million ha of forest are estimated by Houghton (2010, unpublished data; global results reported in Friedlingstein et al. 2010) to be managed, that is, recovering from wood harvest or in the fallow portion of shifting cultivation. Subtracting this area of managed forests from the total area of tropical forests yields the area of intact forests (1,392 million ha) and thus a net carbon sink in these unmanaged tropical forests of 1.19 PgC yr^{-1} (Table 2.3).

The carbon sink in the world's inventoried forests was 2.4 PgC yr^{-1} (1.22 in temperate zone and boreal forests and 1.19 PgC yr^{-1} in the unmanaged forests of the tropics). In contrast, the net terrestrial sink calculated from the global carbon balance (Section 2.2) was 1.3 PgC yr^{-1} in the same period (1990–2007). The difference implies a source of 1.1 PgC yr^{-1} either in ecosystems other than forests or in the managed forests of the tropics not included in the inventories. The source/sink for managed tropical forests is determined from an analysis of land use change, described below (Houghton 2010, unpublished data).

2.4 Land Use Change (Direct Anthropogenic Effects)

Managed lands, or those lands directly affected by land use and land cover change (LULCC), can lead to either sources or sinks of carbon, and many analyses of LULCC have attempted to estimate those sources and sinks. "Land use" refers to management within a land cover type. For example, the harvest of wood does not change the designation of the land as forest although the land may be temporarily treeless. "Land cover change," in contrast, refers to the conversion of one cover type to another, for example, the conversion of forest to cropland. Note that "deforestation" as used in this chapter refers to the conversion of forest to another land cover. Logging, even clear-cut logging, is not deforestation unless it is followed by a land use without forest cover, for example, cropland.

Ideally, LULCC would be defined broadly to include not only human-induced changes in land cover, but all forms of land management (e.g., techniques of harvesting). The reason for this broad ideal is that the net flux of carbon attributable to management is that portion of a terrestrial carbon flux that might qualify for credits and debits under a post-Kyoto agreement. However, it is perhaps impossible to separate management effects from natural and indirect effects (e.g., CO_2 fertilization, N deposition, or the effects of climate change). Furthermore, the ideal requires more data, at higher spatial and temporal resolutions, than have been practical (or possible) to assemble at the global level. Thus, most analyses of the effects of LULCC on carbon storage have focused on the dominant (or documentable) forms of management and, to a large extent, ignored others.

Recent estimates of the flux of carbon from LULCC are shown in Figure 2.2. Most of these emissions in recent decades have been from the tropics, while the net annual flux of carbon from regions outside the tropics has been nearly zero (Houghton 2010, unpublished data). This near neutrality does not indicate a lack of activity outside the tropics. Rather, the sources of carbon from wood harvest are largely balanced by the sinks in regrowing forests harvested in previous years. Annual gross emissions and rates of uptake from LULCC are nearly as great in temperate and boreal regions as they are in the tropics (Richter and Houghton 2011). Rates of wood harvest, for example, are nearly the same in both regions. The main difference between the two regions is that forests are being lost in the tropics, while forest area has been expanding in Europe, China, and the United States.

The global net flux of carbon from LULCC based on these estimates is approximately 1.0 PgC yr^{-1} for the last three decades and 1.1 PgC yr^{-1} for the years 2000–2009 (Houghton 2010, unpublished data). Forests accounted for 90%–95% of this net source, and the global carbon budget is essentially balanced: the emissions from LULCC in the tropics (1.3 PgC yr^{-1}) are more than offset by a sink in the forests of all regions (2.4 PgC yr^{-1}) as determined from forest inventories (see more details in Section 2.4.3).

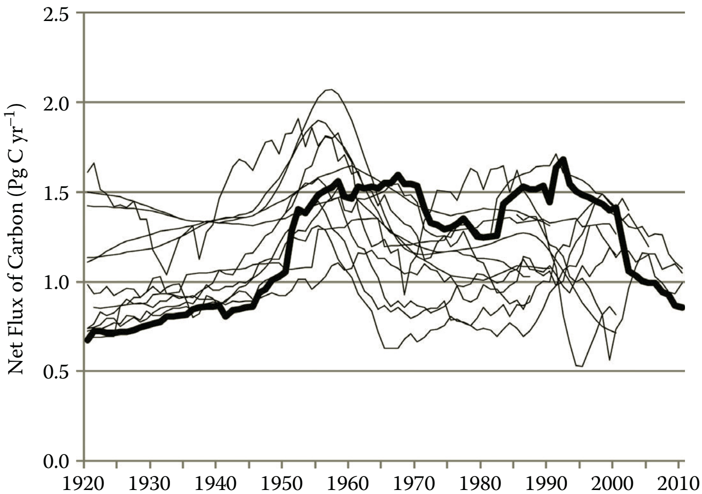


FIGURE 2.2
Recent estimates of the net emissions of carbon from land use and land cover change (LULCC). Houghton's estimate (2010, unpublished data), which is used as an example throughout this chapter, is highlighted.

The discussion below focuses on identifying the reasons underlying differences among the many estimates in Figure 2.2. Differences are grouped into two major categories: (1) data for rates of LULCC and carbon density and (2) the types of LULCC processes included in the analyses.

2.4.1 Data Used to Define Changes in Forest Area and Carbon Density

All of the approaches for calculating the emissions of carbon from LULCC consider the areas affected (e.g., deforested or reforested) and the emission coefficients (carbon lost or gained per hectare following a change in land management). The approaches differ, first, in the data used to define changes in the areas of croplands and pastures; and, second, in the way carbon stocks and changes in carbon stocks are estimated (some are modeled; others are specified from observations).

A significant difference among approaches is the spatial resolution of the analysis. The nonspatial approach of bookkeeping models (e.g., Houghton 2010, unpublished data) cannot represent the spatial heterogeneity of biomes, and thus the emissions calculated with mean carbon densities for large regions may be biased. In contrast, spatially explicit information on changes in forest area, especially when combined with spatially explicit estimates of biomass density, should provide more accurate estimates of the carbon emissions from LULCC. Compared with nationally aggregated estimates of change used in bookkeeping models, spatially explicit data reduce uncertainties by identifying where and which forests types have undergone change.

As biomass density can vary substantially within a country and across forest types, satellite data provide a clear benefit. The spatial colocation of deforestation with carbon density will greatly improve the precision of carbon emissions, including the sources and sinks from ecosystems not directly affected by land use or land cover change (Houghton and Goetz 2008).

Note that although process-based models are spatially explicit (Pongratz et al. 2009; Shevliakova et al. 2009), the historical data for simulating land cover change rarely are. Maps, at varying resolutions, exist for many parts of the world, but only during the satellite era (Landsat began in 1972) are spatial data on land cover change available, in theory. In fact, there are many holes in the coverage of the earth's surface until 1999 when the first global acquisition strategy for moderate spatial resolution data was undertaken with the Landsat Enhanced Thematic Mapper Plus Sensor (Arvidson et al. 2001). The long-term acquisition plan of Landsat ETM+ data ensures annual global acquisitions of the land surface. However, cloud cover and phenological variability limit the ability to provide annual global updates of forest extent and change. The only other satellite system to provide global coverage of the land surface is the ALOS PALSAR instrument, which also includes an annual acquisition strategy for the global land surface (Rosenqvist et al. 2007).

Remote sensing–based information on recent land cover change has been combined with regional statistics, such as from FAO, to reconstruct spatially explicit land cover reconstructions covering more than the satellite era (Ramankutty and Foley 1999; Goldewijk 2001; Pongratz et al. 2008). Historical changes in LULCC are important for today's sources and sinks of carbon because the emissions of carbon from deforestation are not instantaneous. Woody debris generated at the time of disturbance may take decades to decompose. Similarly, the uptake of carbon by secondary forests continues for decades and centuries after these forests begin to grow. In the absence of spatial data on biomass density, the long-term history of LULCC is necessary to simulate changes in biomass density resulting from management. The biomass density of forests cleared for agriculture today depends, in large part, on how long those forests have had to recover from previous harvests. On the other hand, if spatial estimates of biomass density are obtained directly, documentation of disturbance history may no longer be required.

2.4.2 Other Differences among Estimates of Carbon Emissions from Land Use Change

Besides differences in data used to estimate deforestation rates and carbon density, the variability in flux estimates also results from the types of land use included. All of the analyses in Figure 2.2 included deforestation, either by using satellite data on forest cover or by inferring changes in forest area by combining data on the expansion and abandonment of agricultural area (cropland and pasture) with information on the distribution of natural vegetation.

Forest degradation: Some of the estimates in Figure 2.2 also included forest management, wood harvest, or other management practices that change the carbon density within forests. The reduction in biomass density within forests as a result of land use is defined here as degradation. Logging in Amazonia, for example, added 15%–19% to the emissions of carbon from deforestation alone (Huang and Asner 2010). For all the tropics, harvests of wood and shifting cultivation, together, added 28% to the net emissions calculated on the basis of land cover change alone (Houghton 2010, unpublished data). Globally, these rotational uses of land added 32%–35% more to the net emissions from deforestation (Shevliakova et al. 2009). Thus, those analyses that have included wood harvest and shifting cultivation yield higher, and presumably more comprehensive, estimates of the net emissions from LULCC.

Indirect anthropogenic effects: While bookkeeping models use rates of growth and decay that are fixed for different types of ecosystems, process-based models simulate the processes of growth and decay as a function of climate variability and trends in atmospheric composition. Because effects are partly compensating (e.g., deforestation under increasing CO_2 leads to higher emissions because CO_2 fertilization increases carbon stocks, but regrowth is also stronger as CO_2 fertilization has a more pronounced impact on regrowing than on mature forest), a CO_2 fertilization effect is not likely to be a major factor in accounting for differences among emission estimates. In one study, the combined effect of changes in climate and atmospheric composition increased LULCC emissions by about 8% over the industrial era (Pongratz et al. 2009). There are doubtlessly other interactions as well between environmental changes and management. These interactions make attribution difficult; that is, are the sources and sinks the result of management or the indirect effect of environmental change?

There is another (indirect) effect of deforestation. As forests are lost, the sink capacity on land is diminished. This effect has been called the "net land use amplifier effect" (Gitz and Ciais 2003) and the "loss of additional sink capacity" (Pongratz et al. 2009). In models, the strength of this effect depends on the atmospheric CO_2 concentration. These indirect effects account for a portion of the variability among emission estimates.

2.4.3 Sources and Sinks of Carbon from Land Use Change

The sources and sinks of carbon from LULCC are significant in the global carbon budget (Table 2.2). Globally, the annual emissions of carbon from LULCC were larger than the emissions from fossil fuels until ~mid twentieth century. Since ~1945, the emissions from fossil fuels have increased dramatically, while the emissions from land use have remained nearly constant at 1–1.5 PgC yr^{-1}. Thus the contribution of LULCC to anthropogenic carbon emissions has varied from about 33% of total emissions over the last

150 years (Houghton 1999) to about 12% in 2008 (van der Werf et al. 2009). The declining fraction is largely the result of the accelerated rise in fossil fuel emissions.

It is important to note that these emissions from LULCC are net emissions. They include both sources and sinks of carbon from land use—sources when forests are converted to croplands or pastures and sinks when forests regrow following harvest or following abandonment of croplands or pastures. In fact, the gross sources and sinks from land use and recovery are two to three times greater than the net source (Richter and Houghton 2011). The error associated with the net flux of carbon from LULCC is thought to be ±0.7 PgC yr^{-1} (Le Quéré et al. 2009).

It should be clear that the net flux of carbon from LULCC is not equivalent to the "emissions of carbon from deforestation," although the terms are used interchangeably in the literature. The former includes other forms of management besides deforestation, for example, degradation of forests. Further, the net flux of carbon from LULCC includes sources and sinks of carbon from nonforests. Cultivation of prairie soils, for example, results in a loss of soil carbon unrelated to forests. Over the last 150 years, forests accounted for between 84% and 96% of the annual net flux from LULCC. The fraction has varied through history; in recent decades forests have accounted for 90%–95%.

2.4.3.1 Land Use Change in Tropical Forests

Recall that managed forests were not included in the forest inventories of the tropics (Section 2.3). The net carbon balance for managed forests was determined by simulating LULCC, specifically deforestation for crops, pasture, and shifting cultivation; reforestation following abandonment of these land uses; and harvest of wood products (Houghton 2010, unpublished data). LULCC in the tropics is estimated to have caused a net source of 1.3 (±0.7) PgC yr^{-1} over the period 1990–2007. The gross emissions were 2.9 PgC yr^{-1} (from deforestation and harvests); gross uptake in secondary forests averaged 1.6 ± 0.5 PgC yr^{-1} (Table 2.3).

2.4.3.2 Land Use Change in Boreal and Temperate Zone Forests

The forest inventories of boreal and temperate zone forests included both managed and unmanaged forests and thus provide enough information to determine the net effect of forests in the carbon cycle. This inventory-based estimate of flux is very different from the flux determined from analysis of LULCC. The net sink obtained from forest inventories was 1.22 PgC yr^{-1} over the period 2000–2007 (Table 2.3). In contrast, the net sink obtained from LULCC was nearly zero (a net sink of 0.04 PgC yr^{-1}), with gross emissions of 1.52 PgC yr^{-1} and a gross sink of 1.56 PgC yr^{-1} (Houghton 2010, unpublished data). The major reason for the large difference in the two estimates of the sink, aside from errors, is believed to be that forests are accumulating carbon in response to environmental changes, and these environmental responses are not included in Houghton's (2010, unpublished data) bookkeeping model (see Section 2.5.1.2).

2.4.3.3 Global Summary of LULCC

The world's forests were a net sink of 1.1 PgC yr^{-1} over the period 2000–2007 (Pan et al. 2011) (Table 2.3). This net sink includes a source of 1.3 PgC yr^{-1} from deforestation and harvests (LULCC) and a sink of 2.4 PgC yr^{-1} measured in forest inventories. These estimates yield a balanced global carbon budget. The net terrestrial sink (1.3 PgC for the period 1990–2009) is approximately equal to the net sink in forests (1.1 PgC yr^{-1}).

The gross uptake of carbon by the world's forests was estimated by Pan et al. (2011) to be 4.05 ± 0.67 PgC yr^{-1} (2.41 in intact forests and 1.64 in managed forests in the tropics). But this estimate of a gross uptake is an underestimate because the sink of 1.22 PgC yr^{-1} in temperate zone and boreal forests is a net sink, not a gross sink. Adding the gross uptake in these forests, obtained from LULCC (Houghton 2010, unpublished data), yields a gross uptake of 5.61 PgC yr^{-1} (4.05 + 1.56) for the world's forests.

2.5 Global Carbon Cycle Revisited: Residual Terrestrial Sink

The source of carbon from LULCC explains a part of the net terrestrial carbon flux and, thereby, helps define a different residual terrestrial flux (Figure 2.3). Figure 2.3 is similar to Figure 2.1 except the net terrestrial flux of Figure 2.1 has been broken into a net flux from land use change (always a net source historically) and a terrestrial residual flux. The residual flux is calculated by difference, just as the net terrestrial flux was calculated by difference in Figure 2.1. It is noteworthy that the net terrestrial flux and the LULCC flux were approximately equal before ~1925. Before this date the LULCC flux *was* the net terrestrial flux. Only in recent decades has there been another terrestrial sink unexplained by LULCC. It should be recognized that terrestrial carbon models calculate an annual carbon sink consistent with the sink calculated by difference (Le Quéré et al. 2009). Differences among estimates for the future, however, suggest that those models are not reliable enough to predict the future terrestrial carbon sink/source (Cramer et al. 2001; Friedlingstein et al. 2006).

In sum, forests account (1) for 90%–95% of the net emissions from LULCC and (2) for nearly all the residual terrestrial sink (Pan et al. 2011). Thus, forests are important, both as a source of carbon to the atmosphere from human activity and as a sink for carbon through natural processes not entirely understood. Obviously, forest management can be used, and is, to

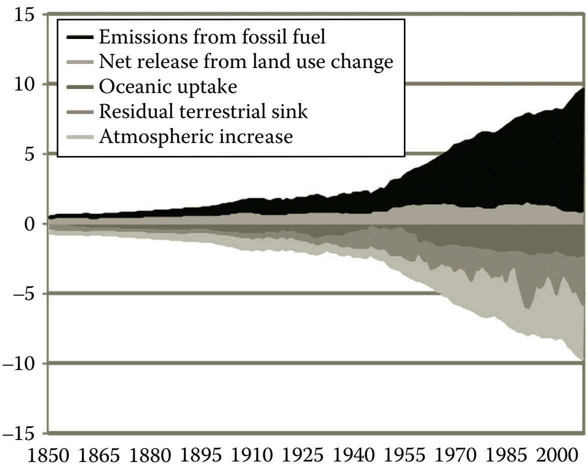


FIGURE 2.3
Annual sources (+) and sinks (–) in the global carbon budget. The terrestrial flux is partitioned into a flux from land use change and a residual terrestrial sink.

accumulate carbon on land (the gross sink from LULCC, globally, is about 3 PgC yr^{-1}) (Richter and Houghton 2011), but the emissions from deforestation have dominated the effects of management to date.

2.5.1 What Explains the Residual Terrestrial Sink?

The residual terrestrial sink incorporates all of the errors from the other terms in the global carbon budget and has an error on the order of 1 PgC yr^{-1}. The analysis of data from forest inventories suggests a net sink of 2.4 PgC yr^{-1} over the period 1990–2007 that was presumably driven by some combination of processes, some already considered in analyses of land use change and others not considered. The sections below consider potential carbon sinks driven by processes not yet included in analyses of land use change.

Aside from cumulative errors, the residual terrestrial sink may be attributed to two types of explanations: (1) omissions of management practices from analyses of LULCC and (2) factors other than management that affect terrestrial carbon storage.

2.5.1.1 Management Effects Not Included in Analyses of Land Use Change

Before discussing aspects of management that may account for the residual terrestrial sink, it is important to recall that the residual flux does *not* include the sinks of carbon in forests regrowing as a result of direct activity (logging, abandonment, etc.). These sinks are part of the global carbon source from LULCC.

Management activities not included in analysis of land use change (e.g., use of fertilizers in forest management) may have increased the storage of carbon on land. Two other examples are given below. To the extent these processes are important, they would decrease the net source calculated from land use change and, thereby, decrease the residual terrestrial sink, as well. A third example *increases* estimates of both terrestrial fluxes.

Aquatic transport: Erosion and redeposition of carbon: One uncertainty with respect to changes in soil carbon with cultivation concerns the fate of carbon lost from soil. A 25%–30% loss of carbon from the top meter in the years following cultivation has been observed repeatedly (Post and Kwon 2000; Guo and Gifford 2002; Murty et al. 2002) and is generally assumed to have been released to the atmosphere. However, some of it may have been moved laterally to a different location (erosion). Much of the transported carbon may be released to the atmosphere through subsequent decomposition, either during transport or once incorporated in sediment. If so, the loss of carbon was counted in analyses of land use change. However, if the organic carbon settles in anaerobic environments and decomposition is inhibited, the carbon will be sequestered, at least temporarily.

The carbon discharged to the oceans is only a fraction of the carbon entering rivers from terrestrial ecosystems by way of soil respiration, leaching, chemical weathering, and physical erosion. Although most of the carbon is released to the atmosphere in transport, as much as 0.6 PgC may be buried in the sediments of floodplains, lakes, reservoirs, and wetlands (Berhe et al. 2007; Tranvik et al. 2009; Aufdenkampe et al. 2011). If the sink includes some of the observed loss of carbon from the top meter of soil, then the emissions of carbon to the atmosphere from land use change have been overestimated. The estimated sink from erosion/deposition is large, responsive to both land use change and changes in climate, and ought to be considered in the global carbon balance. Furthermore, this buried carbon is important as a potential source of methane. Freshwater ecosystems release an estimated 0.1 PgC yr^{-1} as methane. The carbon emissions are small, but the radiative emissions are enough to account for 25% of the estimated terrestrial sink (Bastviken et al. 2011).

Woody encroachment: Another possible explanation for the residual sink is "woody encroachment." The expansion of trees and woody shrubs into herbaceous lands, although it cannot be attributed definitively to natural, indirect (climate, CO_2), or direct effects (fire suppression, grazing), is, nevertheless, happening in many regions. Scaling it up to a global estimate is problematical, however (Archer et al. 2001), in part because the areal extent of woody encroachment is unknown and difficult to measure. Also, the increase in vegetation carbon stocks observed with woody encroachment is in some cases offset by losses of soil carbon (Jackson et al. 2002). Finally, woody encroachment may be offset by its reverse process, woody elimination, an example of which is the fire-induced spread of cheatgrass (*Bromus tectorum*) into the native woody shrub lands of the Great Basin in the western United States (Bradley et al. 2006).

The net effect of woody encroachment and woody elimination is, thus, uncertain, not only with respect to net change in carbon storage, but also with respect to attribution. It may be an unintended effect of management, or it may be a response to indirect or natural effects of environmental change.

Emissions from draining and burning of peatlands: Not all of the processes left out of analyses of land use change would reduce the net carbon source if they were included. Some processes act to increase the emissions and increase the residual terrestrial sink as well. One such process is the draining and burning of tropical swamp forests for the establishment of oil palm plantations in Southeast Asia. This use of land is thought to add 0.3 PgC yr^{-1} to the net emissions of carbon from land use change (Hooijer et al. 2010). The elevated carbon emissions from these and other wetlands have not been included in global estimates of emissions from land cover change.

2.5.1.2 Indirect and Natural Effects (Processes Not Directly Related to Management)

Two other processes besides the direct effects of management (LULCC) account for changes in terrestrial carbon storage: indirect effects (rising concentrations of CO_2, deposition of reactive nitrogen, climate change) and natural effects, including changes in disturbance regimes (Marlon et al. 2008).

Effects of CO_2, N deposition, and climate change on carbon storage of forests (*indirect anthropogenic effects*): Three environmental factors are generally thought to explain increases in plant productivity and, thereby, carbon storage: CO_2 fertilization, nitrogen deposition, and changes in climate (Schimel 1995). Increased concentrations of CO_2 are thought to have caused increased biomass density in tropical forests (Lewis et al. 2004). Nitrogen deposition is believed to be especially important in the northern mid latitudes (Thomas et al. 2010). And changes in temperature and moisture are important, particularly through earlier and longer growing seasons. Competition among these factors to explain the residual terrestrial sink has existed for nearly as long as the sink has been recognized. The relative strengths are unknown.

Changes in disturbance regimes: Natural disturbance regimes (including recovery) may themselves change over decades or centuries, causing carbon to accumulate during some periods and to be lost during others (Marlon et al. 2008; Wang et al. 2010). A reduction in disturbances over the last decades may have shifted more forests to a phase of recovery with attendant sinks. It must be noted, however, that in many regions the effects of climate change (droughts and fires) appear to have caused additional carbon to be lost rather than accumulated (Gillett et al. 2004; Westerling et al. 2006; Kurz et al. 2008). Apparently the increased releases of carbon from fires, storms, diseases, and logging are offset by regrowth or enhanced growth elsewhere.

2.5.2 Sources and Sinks of Carbon in the Net Residual Terrestrial Sink

Like the net source of carbon from LULCC, the residual terrestrial sink is also a *net* sink, including both sources and sinks of carbon. Its existence today does not imply that it will continue to grow, or that it will continue at all. Model experiments suggest that the drying effects of a warmer climate may cause dieback of tropical forests in Amazonia (Cox et al. 2000), a prediction looking more reasonable after two 100-year droughts occurred there in the last decade (Phillips et al. 2009; Lewis et al. 2011). In boreal forests, too, not only have fires increased in recent decades (Stocks et al. 2003; Kasischke and Turetsky 2006; Westerling et al. 2006), but the productivity of the forests, at first observed to have increased, has declined since ~1990 (Goetz et al. 2007), most likely in response to drought stress. And an unusually large fire in the Alaskan tundra (Mack et al. 2011) may foreshadow increased sources of carbon from those ecosystems too.

2.5.3 Is the Residual Terrestrial Sink Changing? Or Will It Change?

Remarkably, the *proportions* of anthropogenic carbon emissions (fossil fuel and land use change) taken up by the atmosphere, oceans, and land have changed little in the last 50 years. In other words, the annual accumulations of carbon on land and in the oceans have increased in proportion to emissions. Over the years 2000–2009, the annual emissions from fossil fuels and land use change accumulated in the atmosphere (~47%), the oceans (~26%), and land (~27%) (Table 2.2). There is little sign of any saturation of these sinks. Some scientists argue that the airborne fraction (the increase in the atmosphere divided by total emissions) has increased slightly, suggesting that the sinks may be beginning to saturate (Canadell et al. 2007; Le Quéré et al. 2009), but others argue that that increase cannot be observed against the year-to-year variability in the airborne fraction and the uncertainty of the land use flux (Knorr 2009).

There are other problems with interpreting the airborne fraction. Changes in the airborne fraction may be influenced by the nonlinear responses of oceanic uptake to changes in the rate of emissions (Gloor et al. 2010). The oceanic sink is not determined by a single carbon reservoir that mixes infinitely fast, as assumed in the linear analyses. Rather, variations in the "CO_2 sink rate," if calculated with a single-box model, will result from variations in the growth rate of the sources, with no change in the rate constants of ocean mixing. The land and ocean sinks may, indeed, be slowing, but demonstrating it through observations of the airborne fraction will be difficult.

2.6 Which Sources and Sinks of Carbon Are Observable from Space?

Data from satellites have been used successfully to measure changes in forest area, but it has been more difficult to determine from satellite data alone whether those changes are anthropogenic or not, and, if they are, whether they represent a land cover change (e.g., conversion of forest to cropland) or a land use (logging and subsequent recovery).

Aside from changes in forest area, however (and changes in area are the changes that involve the greatest changes in carbon), there are other issues that need attention. This chapter concludes with a discussion of three questions:

- Can changes in terrestrial carbon be measured from space?
- Can the net carbon balance of terrestrial ecosystems be more easily measured if sources and sinks are unevenly distributed?
- Can losses and gains of terrestrial carbon be attributed to direct management, as opposed to indirect environmental effects?

2.6.1 Can Changes in Terrestrial Carbon Be Measured from Space?

For aboveground woody biomass, although different methods have yielded wildly different estimates for large regions in the past (Houghton et al. 2001), new satellite-based methods look promising (Hall et al. 2011; Le Toan et al. 2011). Mapping change in biomass density over large regions is in its infancy, and testing maps over large areas remains a challenge, but instruments coming online will most likely enable measurements at higher and higher spatial resolutions. The new study by Baccini et al. (2011) represents a step in this direction.

In contrast to aboveground biomass, changes in belowground carbon stocks, woody debris, and wood products will have to be modeled, but the good news is that changes in aboveground biomass account for ~90% of the net carbon flux (2000–2009), while changes in soil carbon, wood products, and woody debris account for only 20%, 10%, and 0% of the net flux, respectively (Figure 2.4). The sum is more than 100% because during this interval carbon accumulated in wood products, while it was lost from biomass and soils.

Large, rapid changes in aboveground biomass are more easily observed than small, slow changes. This observation means that satellites are biased toward detecting deforestation while missing the slower rates of accumulation of biomass during growth.

The existence of delayed fluxes implies that methods for estimating flux must include data on historical land cover activities and associated information on the fate of cleared carbon. Such historical data are not included in all

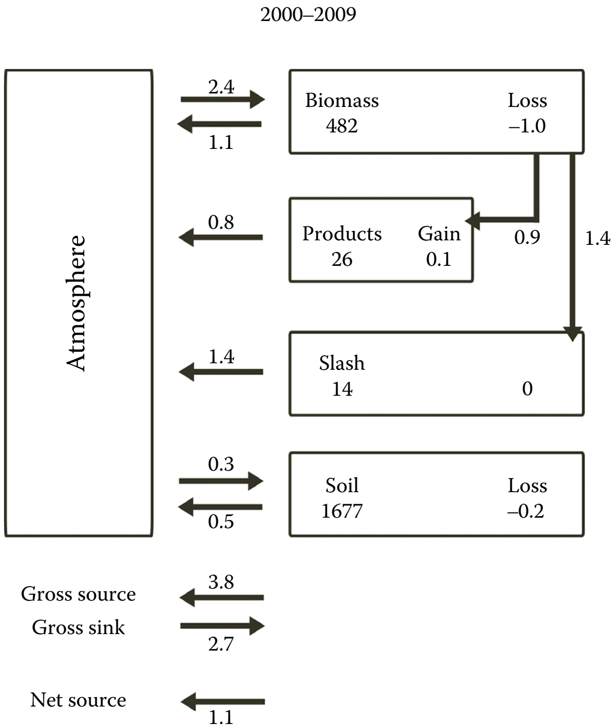


FIGURE 2.4
Average annual flows of carbon (PgC yr^{-1}) in the world's terrestrial ecosystems as a result of land use change over the period 2000–2009. The sum of exchanges with the atmosphere is equivalent to the sum of changes in the four pools (a flux of 1.1 PgC yr^{-1} from land to atmosphere).

analyses, especially in those using remote sensing data where information is available only since the 1970s at best. How far back in time does one need to conduct analyses in order to estimate current emissions accurately, or, alternatively, how much are current emissions underestimated by ignoring legacy fluxes? Ramankutty et al. (2007) explored these questions using a sensitivity analysis of Amazonia. Their "control" study used historical land use information beginning in 1961 and calculated annual fluxes for the period 1961–2003. When they repeated the analysis ignoring historical land use prior to 1981, they underestimated the 1990–1999 emissions by 13%; when they repeated it ignoring data prior to 1991, they underestimated emissions by 62%. However, if more of the cleared carbon was burned and less decayed, the underestimated emissions were reduced to 4% and 21%, respectively.

In another analysis of deforestation and reforestation in Amazonia, Houghton et al. (2000) found that the annual emissions of carbon from accumulated wood products and slash were three to four times higher than the annual emissions from burning. The legacy from secondary forests was also large in this analysis, accounting for an annual sink as large as the annual source from burning. Sources and sinks of carbon from changes in aboveground biomass are amenable to measurement. Sources from accumulated wood products or downed woody debris will require historical information and modeling.

2.6.2 Can the Net Carbon Balance of Land Be More Easily Measured if Sources and Sinks Are Unevenly Distributed?

In the worst case, the net terrestrial sink is distributed evenly over the land surface and, thus, is so small per hectare that it would to be impossible to measure. On the other hand, many disturbances involve changes large enough to be observed remotely. Furthermore, the gross fluxes from disturbance and recovery are two to three times greater and thus more readily identified than the net source/sink (Richter and Houghton 2011). Several recent studies suggest that changes in forest biomass are more frequent than generally expected. More than half of the hectares of an old-growth tropical forest in Costa Rica, for example, showed (with airborne lidar) either losses or gains of carbon over 7 years (Dubayah et al. 2010), and a recent study with Landsat showed that small gaps associated with tree falls in Central Amazonia were numerous enough to account for an area equivalent to 40% of that region's annual deforestation (Negrón-Juárez et al. 2011).

These results on the one hand, raise the hope that change may be more common, and thus more readily detected and measured, than expected. That is, the net terrestrial sink is *not* distributed evenly over the land surface. On the other hand, the errors associated with the more easily measured sources and sinks may make estimation of a net global change no more accurate than it would be if the change were evenly distributed over the terrestrial surface. Furthermore, the recent examples of fine-scale changes in carbon density may be no more than "noise" in longer term trends or large-area averages. Changes might be better observed over large regions using coarse resolution imagery, sampled with high-resolution lidar, for a more accurate estimate of average change. If the goal is to understand individual trees in a stand, coarse resolution would, of course, not be appropriate.

2.6.3 Can Losses and Gains of Terrestrial Carbon Be Attributed to Direct Management, as Opposed to Indirect Environmental Effects?

Besides the policy reasons for distinguishing direct anthropogenic effects from environmental effects, the scientific reason for attribution is to better understand the current global carbon cycle and to better predict future changes. One goal is to understand the individual processes responsible for what is now referred to as the residual terrestrial flux. The global carbon budget has advanced from recognizing a single net terrestrial flux of carbon (Figure 2.1) to recognizing two terrestrial fluxes: an LULCC flux and a residual terrestrial flux (Figure 2.3). Both of these net fluxes can be further divided, for example, into gross fluxes or into different causal mechanisms. Changes driven by natural disturbances and recovery (structural changes) are clearly different from changes driven by enhanced or retarded growth rates (metabolic changes). Some will lend themselves to observation from space; others will remain in the residual category until models are good enough or data are specific enough to enable additional distinctions.

About the Contributor

Richard A. Houghton is a senior scientist at the Woods Hole Research Center in Falmouth, Massachusetts. The Center is an independent, nonprofit institute focused on environmental science, education, and policy. Houghton has studied the interactions of terrestrial ecosystems with the global carbon cycle and climate change for more than 30 years, in particular documenting changes in land use and determining the sources and sinks of carbon attributable to land management. He has participated in the IPCC Assessments of Climate Change and the U.S. Climate Change Science Program's *First State of the Carbon Cycle Report (SOCCR): The North American Carbon Budget and Implications for the Global Carbon Cycle*. He received his PhD in ecology from the State University of New York at Stony Brook in 1979 and has worked as a research scientist at Brookhaven National Laboratory in New York and the Marine Biological Laboratory in Woods Hole, Massachusetts. He has been at the Woods Hole Research Center since 1987, serving for 2 years (1993–1994) as a visiting senior scientist at the NASA headquarters in Washington, DC.

References

Archer, S., T.W. Boutton, and K.A. Hibbard. 2001. Trees in grasslands: biogeochemical consequences of woody plant expansion. In *Global Biogeochemical Cycles in the Climate System*, ed. E.-D. Schulze, S.P. Harrison, M. Heimann, E.A. Holland, J. Lloyd, I.C. Prentice, and D. Schimel, 115–137. Academic Press, San Diego, CA.

Arvidson, T., J. Gasch, and S.N. Goward. 2001. Landsat 7's long-term acquisition plan—an innovative approach to building a global imagery archive. *Remote Sensing of Environment* 78:13–26.

Aufdenkampe, A.K., E. Mayorga, P.A. Raymond, J.M. Melack, S.C. Doney, S.R. Alin, R.E. Aalto, and K. Yoo. 2011. Riverine coupling of biogeochemical cycles between land, oceans, and atmosphere. *Frontiers in Ecology and Environment* 9:53–60.

Baccini, A., S.J. Goetz, W. Walker, N.T. Laporte, M. Sun, D. Sulla-Menashe, J. Hackler, et al. 2011. New satellite-based estimates of tropical carbon stocks and CO_2 emissions from deforestation. *Nature Climate Change* 2:182–185.

Bastviken, D., L.J. Tranvik, J.A. Downing, P.M. Crill, and A. Enrich-Prast. 2011. Freshwater methane emissions offset the continental carbon sink. *Science* 331:50.

Beer, C., M. Reichstein, E. Tomelleri, P. Ciais, M. Jung, N. Carvalhais, C. Rödenbeck, et al. 2010. Terrestrial gross carbon dioxide uptake: Global distribution and covariation with climate. *Science* 329:834–838.

Berhe, A.A., J. Harte, J.W. Harden, and M.S. Torn. 2007. The significance of the erosion-induced terrestrial carbon sink. *BioScience* 57:337–347.

Bradley, B.A., R.A. Houghton, J.F. Mustard, and S.P. Hamburg. 2006. Invasive grass reduces aboveground carbon stocks in shrublands of the Western US. *Global Change Biology* 12:1815–1822.

Canadell, J.G., C. Le Quéré, M.R. Raupach, C.B. Field, E.T. Buitenhuis, P. Ciais, T.J. Conway, N.P. Gillett, R.A. Houghton, and G. Marland. 2007. Contributions to accelerating atmospheric CO_2 growth from economic activity, carbon intensity, and efficiency of natural sinks. *Proceedings of the National Academy of Sciences* 104:18866–18870.

Cox, P.M., R.A. Betts, C.D. Jones, S.A. Spall, and I.J. Totterdell. 2000. Acceleration of global warming due to carbon-cycle feedbacks in a coupled climate model. *Nature* 408:184–187.

Cramer, W., A. Bondeau, F.I. Woodward, I.C. Prentice, R.A. Betts, V. Brovkin, P.M. Cox, et al. 2001. Global response of terrestrial ecosystem structure and function to CO_2 and climate change: results from six dynamic global vegetation models. *Global Change Biology* 7:357–373.

Drummond, M.A. and T.R. Loveland. 2010. Land-use pressure and a transition to forest-cover loss in the eastern United States. *Bioscience* 60:286–298.

Dubayah, R.O., S.L. Sheldon, D.B. Clark, M.A. Hofton, J.B. Blair, G.C. Hurtt, and R.L. Chazdon. 2010. Estimation of tropical forest height and biomass dynamics using lidar remote sensing at La Selva, Costa Rica. *Journal of Geophysical Research* 115:G00E09, doi:10.1029/2009JG000933.

FAO. 2010. *Global Forest Resources Assessment 2010*. FAO Forestry paper 163, FAO, Rome.

Friedlingstein, P., P. Cox, R. Betts, L. Bopp, W. von Bloh, V. Brovkin, P. Cadule, et al. 2006. Climate-carbon cycle feedback analysis: results from the c4mip model intercomparison. *Journal of Climate* 19:3337–3353.

Gillett, N.P., A.J. Weaver, F.W. Zwiers, and M.D. Flannigan. 2004. Detecting the effect of climate change on Canadian forest fires. *Geophysical Research Letters* 31:L18211.

Gitz, V. and P. Ciais. 2003. Amplifying effects of land-use change on future atmospheric CO_2 levels. *Global Biogeochemical Cycles* 17:1024, doi:10.1029/2002GB001963.

Gloor, M., J.L. Sarmiento, and N. Gruber. 2010. What can be learned about carbon cycle climate feedbacks from the CO_2 airborne fraction? *Atmospheric Chemistry and Physics* 10:7739–7751.

Goetz, S.J., M.C. Mack, K.R. Gurney, J.T. Randerson, and R.A. Houghton. 2007. Ecosystem responses to recent climate change and fire disturbance at northern high latitudes: Observations and model results contrasting northern Eurasia and North America. *Environmental Research Letters* 2:045031, doi:10.1088/1748-9326/2/4/045031.

Goldewijk, K. 2001. Estimating global land use change over the past 300 years: The HYDE Database. *Global Biogeochemical Cycles* 15:417–433.

Guo, L.B. and R.M. Gifford. 2002. Soil carbon stocks and land use change: A meta analysis. *Global Change Biology* 8:345–360.

Hall, F.G., K. Bergen, J.B. Blair, R. Dubayah, R. Houghton, G. Hurtt, J. Kellndorfer, et al. 2011. Characterizing 3-D vegetation structure from space: Mission requirements. *Remote Sensing of Environment* 115:2753–2775.

Hooijer A., S. Page, J.G. Canadell, M. Silvius, J. Kwadijk, H. Wösten, and J. Jauhiainen. 2010. Current and future CO_2 emissions from drained peatlands in Southeast Asia. *Biogeosciences-Discussions* 7:1505–1514.

Houghton, R.A. 1999. The annual net flux of carbon to the atmosphere from changes in land use 1850–1990. *Tellus* 51B:298–313.

Houghton, R.A. and S.J. Goetz. 2008. New satellites help quantify carbon sources and sinks. *Eos* 89(43):417–418.

Houghton, R.A., K.T. Lawrence, J.L. Hackler, and S. Brown. 2001. The spatial distribution of forest biomass in the Brazilian Amazon: A comparison of estimates. *Global Change Biology* 7:731–746.

Houghton, R.A., D.L. Skole, C.A. Nobre, J.L. Hackler, K.T. Lawrence, and W.H. Chomentowski. 2000. Annual fluxes of carbon from deforestation and regrowth in the Brazilian Amazon. *Nature* 403:301–304.

Huang, M. and G.P. Asner. 2010. Long-term carbon loss and recovery following selective logging in Amazon forests. *Global Biogeochemical Cycles* 24:GB3028, doi:10.1029/2009GB003727.

Jackson, R.B., J.L. Banner, E.G. Jobbágy, W.T. Pockman, and D.H. Wall. 2002. Ecosystem carbon loss with woody plant invasion of grasslands. *Nature* 418:623–626.

Jeon, S.-B., P. Olofsson, C.E. Woodcock, F. Zhao, X. Yang, and R.A. Houghton. 2011. The effect of land use change on the terrestrial carbon budget of New England. PhD Dissertation, Boston University, Boston, MA.

Kasischke, E.S. and M.R. Turetsky. 2006. Recent changes in the fire regime across the North American boreal region—Spatial and temporal patterns of burning across Canada and Alaska. *Geophysical Research Letters* 33:L09703, doi:10.1029/2006GL025677.

Knorr, W. 2009. Is the airborne fraction of anthropogenic CO_2 emissions increasing? *Geophysical Research Letters* 36:L21710, doi:10.1029/2009GL040613.

Kurz, W.A., C.C. Dymond, G. Stinson, G.J. Rampley, E.T. Neilson, A.L. Carroll, T. Ebata, and L. Safranyik. 2008. Mountain pine beetle and forest carbon feedback to climate change. *Nature* 452:987–990.

Le Quéré, C., M.R. Raupach, J.G. Canadell, G. Marland, L. Bopp, P. Ciais, T.J. Conway, et al. 2009. Trends in the sources and sinks of carbon dioxide. *Nature GeoScience* 2:831–836.

Le Toan, T., S. Quegan, M.W.J. Davidson, H. Balzter, P. Paillou, K. Papathanassiou, S. Plummer, et al. 2011. The BIOMASS mission: Mapping global forest biomass to better understand the terrestrial carbon cycle. *Remote Sensing of Environment* 115:2850–2860.

Lewis, S.L., P.M. Brando, O.L. Phillips, G.M.F. van der Heijden, and D. Nepstad. 2011. The 2010 Amazon drought. *Science* 331:554.

Lewis, S.L., G. Lopez-Gonalez, B. Sonké, K. Affum-Baffo, and T.R. Baker. 2009. Increasing carbon storage in intact African tropical forests. *Nature* 477:1003–1006.

Lewis, S.L., O.L. Phillips, T.R. Baker, J. Lloyd, Y. Malhi, S. Almeida, N. Higuchi, et al. 2004. Concerted changes in tropical forest structure and dynamics: Evidence from 50 South American long-term plots. *Philosophical Transactions of the Royal Society of London, Series B* 359:421–436.

Mack, M.C., M.S. Bret-Harte, T.N. Hollingsworth, R.R. Jandt, E.A.G. Schuur, G.R. Shaver, and D.L. Verbyla. 2011. Carbon loss from an unprecedented Arctic tundra wildfire. *Nature* 475:489–492.

Marlon, J.R., P.J. Bartlein, C. Carcaillet, D.G. Gavin, S.P. Harrison, P.E. Higuera, F. Joos, M.J. Power, and I.C. Prentice. 2008. Climate and human influences on global biomass burning over the past two millennia. *Nature Geoscience* 1:697–701.

Murty, D., M.F. Kirschbaum, R.E. McMurtrie, and H. McGilvray. 2002. Does conversion of forest to agricultural land change soil carbon and nitrogen? A review of the literature. *Global Change Biology* 8:105–123.

Negrón-Juárez, R.I., J.Q. Chambers, D.M. Marra, G.H.P.M. Ribeiro, S.W. Rifai, N. Higuchi, and D. Roberts. 2011. Detection of subpixel treefall gaps with Landsat imagery in Central Amazon forests. *Remote Sensing of Environment* 115:3322–3328, doi:10.1016/j.rse.2011.07.015.

Pan, Y., R.A. Birdsey, J. Fang, R. Houghton, P.E. Kauppi, W.A. Kurz, O.L. Phillips, et al. 2011. A large and persistent carbon sink in the world's forests. *Science* 333:988–993.

Peters, G.P., G. Marland, C. Le Quéré, T. Boden, J.G. Canadell, and M.R. Raupach. 2012. Rapid growth in CO_2 emissions after the 2008–2009 global financial crisis. *Nature Climate Change* 2:2–4.

Phillips, O.L., L.E. Aragão, S.L. Lewis, J.B. Fisher, J. Lloyd, G. López-González, Y. Malhi, et al. 2009. Drought sensitivity of the Amazon rainforest. *Science* 323:1344–1347.

Phillips, O.L., T.R. Baker, L. Arroyo, N. Higuchi, T.J. Killeen, W.F. Laurance, S.L. Lewis, et al. 2004. Pattern and process in Amazon forest dynamics, 1976–2001. *Philosophical Transactions of the Royal Society, Series B* 359:381–407.

Phillips, O.L., S.L. Lewis, T.R. Baker, K.-J. Chao, and N. Higuchi. 2008. The changing Amazon forest. *Philosophical Transactions of the Royal Society, Series B* 363:1819–1828.

Pongratz, J., C. Reick, T. Raddatz, and M. Claussen. 2008. A reconstruction of global agricultural areas and land cover for the last millennium. *Global Biogeochemical Cycles* 22:GB3018, doi:10.1029/2007GB003153.

Pongratz, J., C.H. Reick, T. Raddatz, and M. Claussen. 2009. Effects of anthropogenic land cover change on the carbon cycle of the last millennium. *Global Biogeochemical Cycles* 23:GB4001, doi:10.1029/2009GB003488.

Pongratz, J., C.H. Reick, T. Raddatz, and M. Claussen. 2010. Biogeophysical versus biogeochemical climate response to historical anthropogenic land cover change. *Geophysical Research Letters* 37:L08702, doi:10.1029/2010GL043010.

Post, W.M. and K.C. Kwon. 2000. Soil carbon sequestration and land-use change: processes and potential. *Global Change Biology* 6:317–327.

Ramankutty, N. and J.A. Foley. 1999. Estimating historical changes in global land cover: Croplands from 1700 to 1992. *Global Biogeochemical Cycles* 13:997–1027.

Ramankutty, N., H.K. Gibbs, F. Achard, R. DeFries, J.A. Foley, and R.A. Houghton. 2007. Challenges to estimating carbon emissions from tropical deforestation. *Global Change Biology* 13:51–66.

Richter, D. deB. and R.A. Houghton. 2011. Gross CO_2 fluxes from land-use change: Implications for reducing global emissions and increasing sinks. *Carbon Management* 2:41–47.

Rosenqvist, A., M. Shimada, N. Ito, and M. Watanabe. 2007. ALOS PALSAR: A pathfinder mission for global-scale monitoring of the environment. *IEEE Transactions on Geoscience and Remote Sensing* 45:3307–3316.

Schimel, D.S. 1995. Terrestrial ecosystems and the carbon cycle. *Global Change Biology* 1:77–91.

Shevliakova, E., S.W. Pacala, S. Malyshev, G. Hurtt, P.C.D. Milly, J. Casperseon, L. Sentman, et al. 2009. Carbon cycling under 300 years of land use change: Importance of the secondary vegetation sink. *Global Biogeochemical Cycles* 23:GB2022, doi:10.1029/2007GB003176.

Stocks, B.J., J.A. Mason, J.B. Todd, E.M. Bosch, B.M. Wotton, B.D. Amiro, M.D. Flannigan, et al. 2003. Large forest fires in Canada, 1959–1997. *Journal of Geophysical Research* 108(D1):8149, doi:10.1029/2001JD000484.

Thomas, R.Q., C.D. Canham, K.C. Weathers, and C.L. Goodale. 2010. Increased tree carbon storage in response to nitrogen deposition in the US. *Nature Geoscience* 3:13–17.

Tranvik, L.J., J.A. Downing, J.B. Cotner, S.A. Loiselle, R.G. Striegl, T.J. Ballatore, P. Dillon, et al. 2009. Lakes and reservoirs as regulators of carbon cycling and climate. *Limnology and Oceanography* 54:2298–2314.

van der Werf, G.R., D.C. Morton, R.S. DeFries, J.G.J. Olivier, P.S. Kasibhatla, R.B. Jackson, G.J. Collatz, and J.T. Randerson. 2009. CO_2 emissions from forest loss. *Nature Geoscience* 2:737–738.

Wang, Z., J. Chappellaz, K. Park, and J.E. Mak. 2010. Large variations in southern hemisphere biomass burning during the last 650 years. *Science* 330:1663–1666.

Westerling, A.L., H.G. Hidalgo, D.R. Cayan, and T.W. Swetnam. 2006. Warming and earlier spring increase western U.S. forest wildfire activity. *Science* 313:940–943.

3

Use of Earth Observation Technology to Monitor Forests across the Globe

Frédéric Achard
Joint Research Centre of the European Commission

Matthew C. Hansen
University of Maryland

CONTENTS

3.1 Introduction

As presented in Chapters 1 and 2, forests provide crucial ecosystem services. In this respect, it is important to tackle the technical issues surrounding the ability to produce accurate maps and consistent estimates of forest type, location, area, condition, and changes in these factors at scales from global to local. Remotely sensed data from earth observing satellites are crucial to such efforts. Recent developments in regional and global monitoring of tropical forests from earth observation have profited immensely from changes made to the data policy and conditions of data access imposed by major providers of imagery from earth observing satellites—changes that have made access to suitably processed imagery far easier, far cheaper, and far more wide reaching in terms of both geographic coverage and time. On July 23, 1972, the United States launched Landsat 1. This civilian polar-orbiting imaging satellite carried a four-channel multispectral scanner (MSS), which provided images suitable for many forest mapping applications. Its successor is still flying on the quite remarkable Landsat 5. We thus have an unbroken record of observations stretching back over almost four decades.

Imaging sensors on earth observing satellites measure electromagnetic radiation (EMR) reflected or emitted from the Earth's surface and use these measurements as a source of information concerning our planet's physical, chemical, and biological systems. Satellites in geostationary orbit provide frequent images of a fixed view of one side of Earth (as often as every 15 minutes in the case of Europe's Meteosat second-generation instruments), while those in polar orbits, like Landsat, image the entire planet's surface every day or every couple of weeks or so, depending on the spatial characteristics of the sensor; images with detailed spatial measurements (1–30 m) are usually only available once or twice a month—for example, Landsat 5 and 7 (both still flying at the time of writing) image every 16 days at 30 m resolution, while coarser resolution imagery (e.g., the MODerate resolution Imaging Spectroradiometer [MODIS] sensor on Terra at 250 m or the SPOT satellites' VGT sensor at 1 km) is provided every day. Most satellite sensors record EMR beyond the sensitivity of the human eye-measurements in the near and shortwave infrared wavelengths, for example, help differentiate between vegetation types and condition; shortwave and thermal infrared wavelengths are essential for mapping and monitoring forest fires; and measurements in the microwave wavelengths (from imaging radar systems) can even "see" through clouds.

Because the information is captured digitally, computers can be used to process, store, analyze, and distribute the data; and because the information is an image captured at a particular time and place, it provides a permanent record of prevailing environmental conditions. As the same sensor on the same platform is gathering the images for all points on the planet's surface, these measurements are globally consistent and independent—important attributes where monitoring, reporting, and verification (MRV) linked to multilateral environmental agreements, such as the UN Framework Convention on Climate Change (UNFCCC) or the Convention on Biological Diversity, are concerned.

Earth observation from space has become more widely accepted and widely adopted as well as technologically more and more sophisticated. The latest systems launched, such as the Franco-Italian Pleiades system (the first of which was launched December 17, 2011), combine very high spatial resolution (70 cm) with a highly maneuverable platform, capable of providing an image of any point on the surface (cloud cover permitting) with a 24 h revisit period. Earth observation from space has also become more important due to the significant impact that modern human civilization is having on the Earth—over 7 billion people are putting relentless pressure on our planet, and the forests are certainly feeling this. Forty years ago, the United States was largely the only source of imagery—today there are more than 25 space-faring nations flying imaging systems. In 1972 Landsat 1 was the only civilian satellite capable of imaging Earth at a level of spatial detail appropriate for measuring any sort of quantitative changes in forests—today there are more than 40 satellites on orbit that can provide suitable imagery (or at least they could, *if* they had a suitable data acquisition, archiving, processing, access, and distribution policy). This chapter introduces the use of earth observation technology to monitor forests across the globe.

3.2 Scope of the Book

Monitoring forest areas on anything greater than local or regional scales would be a major challenge without the use of satellite imagery, in particular, for large and remote regions. Satellite remote sensing combined with a set of ground measurements for verification plays a key role in determining loss of forest cover. Technical capabilities and statistical tools have advanced since the early 1990s, and operational forest monitoring systems at the national level are now a feasible goal for most developing countries in the tropics (Achard et al. 2010). Improved global observations can support activities related to multilateral environmental agreements, such as the Reducing Emissions from Deforestation and Forest Degradation (REDD)-plus readiness mechanism of the UNFCCC. While the primary interest of countries in forest cover monitoring would occur at national or subnational levels, global or pan-tropical monitoring can contribute through (1) identifying critical areas of change, (2) helping to establish areas within countries that require detailed monitoring, and (3) ensuring consistency of national efforts. The main requirements of global monitoring systems are that they measure changes throughout all forested area, use consistent methodologies at repeated intervals, and verify results. Verification is usually a combination of finer resolution observations and/or ground observations.

This chapter provides an overview of operational remote sensing approaches used to monitor forest cover over large areas. Many methods of satellite imagery analysis can produce adequate results from global to national scales. One of the key issues for forest cover monitoring is that satellite data need to be interpreted (digitally or visually) for forest cover change, i.e., focusing on the interdependent interpretation of multitemporal imagery to detect and characterize changes. Four general remote sensing–based approaches are currently used for capturing forest cover trends:

1. Statistical sampling designed to estimate deforestation from moderate spatial resolution imagery from optical sensors (typically 10–30 m resolution).
2. Global land cover mapping and identification of areas of rapid forest cover changes from coarse spatial resolution imagery from optical sensors (typically 250 m to 1 km resolution).
3. Nested approach with coarse and moderate spatial resolution imagery from optical sensors, i.e., analysis of wall-to-wall coverage from coarse-resolution data to identify locations of large deforestation fronts for further analysis with a sample of moderate spatial resolution data.
4. Analysis of wall-to-wall coverage from moderate spatial resolution imagery from optical or radar sensors.

The use of moderate-resolution satellite imagery for the historical assessment of deforestation has been boosted by changes to the policy that determines access and distribution of data from the U.S. Landsat archive. In the 1990s, the National Aeronautics and Space Administration (NASA) and the U.S. Geological Survey (USGS) developed a global dataset from the Landsat archives. Initially known as the GeoCover™ program, this became the Global Land Survey (GLS) and provided free and open access to selected scenes covering the whole surface of the planet making up the specific epochs (1990, 2000, 2005, and 2010) for the program. The GLS database is described in Chapter 4 together with the freely available complementary database of coarse-resolution MODIS imagery. In December 2008, the U.S. government revised its Landsat data policy and released the entire Landsat archive at no charge. Together the GLS and the U.S. open access data policy mean that anyone interested in global forest monitoring now has access to an archive of data spanning four decades and covering most points on the Earth's surface multiple times over this period. This powerful resource is now being used for statistical sampling on a global scale. The statistical sampling strategies for the use of moderate-resolution satellite imagery are described in Chapter 5. The technical details of the most prominent forest ecosystem monitoring approaches are provided in Chapters 6 through 14. Finally, Chapter 15 covers the use of synthetic aperture radar (SAR) technology and Chapter 16 gives some perspectives of future satellite remote sensing imagery and technology.

The content of the book is introduced briefly hereafter.

3.3 Use of Moderate Spatial Resolution Imagery

Nearly complete pan-tropical coverage from the Landsat satellites is now available at no cost from the Earth Resources Observation Systems (EROS) Data Center (EDC) of the USGS. A recent product, called the GLS, was derived by reprocessing GeoCover data, a selection of good quality, orthorectified, and geodetically accurate global land dataset of Landsat MSS, Landsat TM, and Landsat ETM+ satellite images with a global coverage, which was created by NASA for the epochs of the mid-1970s at 60 m × 60 m resolution and ca. 1990, ca. 2000, mid-2000s, and ca. 2010 at 28.5 m × 28.5 m resolution.

These GLS datasets play a key role in establishing historical deforestation rates, although in some parts of the tropics (e.g., Western Colombia, Central Africa, and Borneo) persistent cloud cover is a major challenge to using these data. For these regions, the GLS datasets can be complemented by remote sensing data from other satellite sensors with similar characteristics, in particular sensors in the optical domain with moderate spatial resolution (Table 3.1). The GLS datasets are described in full detail in Chapter 4.

3.4 Sampling Strategies for Forest Monitoring from Global to National Levels

An analysis that covers the full spatial extent of the forested areas with moderate spatial resolution imagery, termed "wall-to-wall" coverage, is ideal, but is certainly challenging over very large, heterogeneous areas and has commensurate constraints on resources for analysis. China's Institute for Global Change Studies at Tsinghua University and the National Geomatics Center of China have recently completed a first global wall-to-wall map at 30 m resolution, though this ground-breaking new map is still under validation. For digital analysis with moderate-resolution satellite images at pan-tropical or continental levels, sampling is, as of today, still the norm. Several approaches have been successfully applied by sampling within the total forest area so as to reduce costs of and time spent on analysis. A sampling procedure that adequately represents deforestation events can capture deforestation trends. Because deforestation events are not randomly distributed in space, particular attention is needed to ensure that the statistical design is adequately sampled within areas of potential deforestation (e.g., in proximity to roads or other access networks) using high-density systematic sampling when resources are available. The sampling strategies for forest monitoring from global to national levels are described in Chapter 5.

TABLE 3.1

Availability of Moderate Resolution (20 m × 20 m–50 m × 50 m) Optical Sensors

Nation	Satellite/Sensor	Resolution and Coverage	Feature
United States	Landsat 5 TM	30 m × 30 m 180 km × 180 km	This satellite offered images every 16 days to any satellite receiving station during its 27-year lifetime It stopped acquiring images in November 2011
United States	Landsat 7 ETM+	30 m × 30 m 180 km × 180 km	On May 31, 2003, the failure of the scan line corrector resulted in data gaps outside of the central portion of images (60 km wide)
United States/ Japan	Terra ASTER	15 m × 15 m 60 km × 60 km	Data are acquired on request and are not routinely collected for all areas
India	IRS-P6 LISS-III	23.5 m × 23.5 m 140 km × 140 km	Used by India for its forest assessments
China/Brazil	CBERS-2 HRCCD	20 m × 20 m 113 km swath	Experimental; Brazil uses on-demand images to bolster coverage
United Kingdom	UK-DMC	32 m × 32 m 160 km × 660 km	Commercial (DMCii); Brazil uses alongside Landsat data. Full coverage of sub-Saharan Africa acquired in 2010
France	SPOT-5 HRV	5 m × 5 m/ 20 m × 20 m 60 km × 60 km	Commercial; Indonesia and Thailand use alongside Landsat data
Spain/United Kingdom	Deimos-1 and UK-DMC2	22 m × 22 m 640 km swath	Commercial (DMCii); new version of UK-DMC; launched in July 2009
Japan	ALOS AVNIR-2	10 m × 10 m 70 km × 70 km	Launched in January 2006. Global systematic acquisition plan implemented 2007–2010. Stopped in April 2011

For the Forest Resources Assessment 2010 programme (FRA 2010), the Food and Agriculture Organisation of the UN (FAO) has extended its monitoring of forest cover changes at global to continental scales to complement national reporting. The remote sensing survey (RSS) of FRA 2010 has been extended to all lands. The survey aimed at estimating forest change for the periods 1990–2000–2005 based on a sample of moderate-resolution satellite imagery. The methodology used for this global survey is described in Chapter 7.

3.5 Identification of Hot Spots of Deforestation from Coarse-Resolution Satellite Imagery

Global land cover maps provide a static depiction of land cover and cannot be used to map changes in forest areas due to uncertainty levels that are higher than levels of area changes. However, land cover maps can serve as a baseline against which future change can be assessed and can help locate forest areas that need to be monitored for change.

Coarse spatial resolution (from 250 m × 250 m to 1 km × 1 km) satellite imagery is presently used for global land or forest cover mapping. In the late 1990s, global or pan-continental maps were produced at around 1 km × 1 km resolution from a single data source: the advanced very high-resolution radiometer, or AVHRR sensor (Table 3.2). From 2000 onward, new global land cover datasets were produced at similar resolution—1 km × 1 km—from advanced earth observation sensors (VEGETATION on board SPOT-4 and SPOT-5, and the MODIS, on board the Terra and Aqua platforms). These products, GLC-2000 (Bartholomé and Belward 2005) and MODIS global land cover product (Friedl et al. 2010), allowed for a spatial and thematic refinement of the previous global maps owing to the greater stability of

TABLE 3.2

Main Global Land Cover Maps Derived from Remote Sensing Data from 1 km × 1 km to 300 m × 300 m Spatial Resolution

Map Title	Domain	Sensor	Method
IGBP Discover	Global 1 km	NOAA-AVHRR	12 monthly vegetation indices from April 1992 to March 1993
University of Maryland (UMD)	Global 1 km	NOAA-AVHRR	41 multitemporal metrics from composites from April 1992 to March 1993
TREES	Tropics 1 km	NOAA-AVHRR	Mosaics of single date classifications (1992–1993)
FRA 2000	Global 1 km	NOAA-AVHRR	Updated from the IGBP dataset
MODIS Land Cover Product Collection 4	Global 1 km	TERRA MODIS	12 monthly composites from October 2000 to October 2001
Global Land Cover 2000 (GLC-2000)	Global 1 km	SPOT-VGT	Global 365 daily mosaics for the year 2000
VCF	Global 500 m	TERRA MODIS	Annually derived phenological metrics
MODIS Land Cover Product Collection 5	Global 500 m	TERRA MODIS	12 monthly composites plus annual metrics—version of year 2005 released in late 2008
GlobCover	Global 300 m	Envisat MERIS	6 bimonthly mosaics from mid-2005 to mid-2006

the platforms and spectral characteristics of the sensors. An international initiative was also carried out to harmonize existing and future land cover datasets at 1 km resolution to support operational observation of the Earth's land surface (Herold et al. 2006).

More recently, new global land cover datasets at finer spatial resolution (from 250 m × 250 m to 500 m × 500 m) were generated from TERRA-MODIS or ENVISAT-MERIS sensors. The two key products at this scale are the vegetation continuous field (VCF) product (Hansen et al. 2005) and the GlobCover map (Arino et al. 2008). The MODIS-derived VCF product depicts subpixel vegetation cover at a spatial resolution of 500 m × 500 m. The systematic geometric and radiometric processing of MODIS data has enabled the implementation of operational land cover characterization algorithms. Currently, 10 years (2000–2010) of global VCF tree cover are now available to researchers and are being incorporated into various forest cover and change analyses. The 2005 version of the MODIS global land cover product has been generated at 500 m × 500 m resolution, with substantial differences from previous versions arising from increased spatial resolution and changes in the classification algorithm (Friedl et al. 2010). The GlobCover initiative produced a global land cover map using the 300 m resolution mode from the MERIS sensor onboard the ENVISAT satellite. Data have been acquired from December 1, 2004, to June 30, 2006, and then during the full year 2009. A global land cover map was generated from these data from automatic classification tools using equal-reasoning areas. This product has complemented previous global products and other existing comparable continental products, with improvement in terms of spatial resolution. These global products can also be used as complementary forest maps (Figure 3.1) when they do not already exist at the national level, in particular, for ecosystem stratification to help in the estimation of forest biomass through spatial extrapolation methods.

Static forest cover maps are particularly useful as a stratification tool in developing sampling approaches for forest change estimation. For such purposes, reporting the accuracy of these products is essential through the use of agreed protocols. The overall accuracies of the GLC-2000, MODIS, and GlobCover global land cover products have been reported at 68%, 75%, and 73% respectively, though it is important to remember that these accuracy figures relate to all classes of land cover—the accuracy with which forest cover types are mapped are higher than these overall averages.

A first global map of the main deforestation fronts in the 1980s and 1990s has been produced in the early 2000s (Lepers et al. 2005). This map combines the knowledge of deforestation fronts in the humid tropics using expert knowledge, available deforestation maps, and a time-series analysis of tree cover based on NOAA AVHRR 8 km resolution data. In this exercise, the use of expert knowledge ensured that areas of major change not detected with the satellite-based approaches were not overlooked. More recently, a more

FIGURE 3.1
(See color insert.) Global forest cover map derived from the GlobCover Land Cover map at 300 m resolution. Forested areas appear in green. (From Arino, O. et al., *ESA Bull.*, 136, 24, 2008; The GlobCover Land Cover map is available from the European Space Agency website at http://ionia1.esrin.esa.int/.)

detailed quantification of gross forest cover loss at a global scale has been produced for the period 2000–2005 from MODIS imagery. MODIS-indicated change was used to guide sampling of Landsat image pairs in estimating forest extent and loss (Hansen et al. 2010). The MODIS forest cover loss mapping method is presented in Chapter 6.

The Brazilian PRODES monitoring system for the Brazilian Amazon also uses a hotspot approach to identify critical areas based on the previous year's monitoring. These critical areas are priorities for analysis in the following year. Other databases such as transportation networks, population changes in rural areas, and the locations of government resettlement program can be used to help identify areas where a more detailed analysis needs to be performed. Since May 2005, the Brazilian government also has been running the DETER (Detecção de Desmatamento em Tempo Real) system which serves as an alert in almost real time (every 15 days) for deforestation events larger than 25 ha. The system uses MODIS data and WFI data on board the CBERS-2 satellite (260 m × 250 m resolution) and a combination of linear mixture modeling and visual analysis. This approach is described in Chapter 8.

3.6 Nested Approach with Coarse- and Moderate-Resolution Data

Analysis of coarse-resolution data can identify locations of rapid and large deforestation fronts, though such data are unsuitable on their own to determine rates of deforestation based on changes in forest area. A nested approach in which wall-to-wall coarse-resolution data are analyzed to identify locations requiring further analysis with moderate-resolution data can reduce the need to analyze the entire forested area within a country. Coarse-resolution data have been available from the MODIS sensor for no cost since 2000 (see Chapter 4 for the description of this dataset). In some cases, it is possible to identify deforestation directly with coarse-resolution data. Clearings for large-scale mechanized agriculture are detectable with coarse-resolution data based on digital analysis. However, coarse spatial resolution data do not directly allow for accurately estimating forest area changes, given that most change occurs at subpixel scales. Small agricultural clearings or clearings for settlements require finer resolution data (<50 m × 50 m) to accurately detect clearings of 0.5–1 ha. A nested approach that takes advantage of both coarse spatial resolution satellite data and the large Landsat data archive to estimate humid tropical forest cover change is presented in Chapter 6. This method employs a fusion of coarse spatial resolution MODIS data and moderate spatial resolution Landsat data to estimate and map forest cover change as in the studies of Hansen et al. (2008; 2010).

Estimates of forest clearing are generated from the relatively fine-scale resolution Landsat and, through the use of the regression models, can be extended to the continuous MODIS data.

3.7 Analysis of Wall-to-Wall Coverage from Moderate Spatial Resolution Optical Imagery

A few large countries or regions, in particular India, the Congo Basin, Brazil, the European Union, the United States, Australia, and the Russian federation, have demonstrated for many years already that operational wall-to-wall systems over very large regions or countries can be established based on moderate-resolution satellite imagery.

The use of satellite remote sensing technology to assess the forest cover of the whole of India began in early 1980s. The first forest map of the country was produced in 1984 at 1:1 million scale by visual interpretation of Landsat data. The Forest Survey of India (FSI) has since been assessing the forest cover of the country on a 2-year cycle. Over the years, there have been improvements both in the remote sensing data and in the interpretation techniques. The 12th biennial cycle has been completed from digital interpretation of satellite data collected from October 2008 to March 2009 by the Indian satellite IRS P6 (sensor LISS III at 23.5 m × 23.5 m resolution) with a minimum mapping unit of 1 ha (FSI 2011). The entire assessment from the procurement of satellite data to the reporting, including image rectification, interpretation, ground truthing, and validation of the changes by the state/province forest department, takes almost 2 years. The interpretation involves a hybrid approach combining unsupervised classification in raster format and onscreen visual interpretation of classes. Accuracy assessment is carried out independently using randomly selected sample points verified on the ground (field inventory data) or with satellite data at 5.8 m × 5.8 m resolution and compared with interpretation results. In the last assessment, 4,291 validation points randomly led to an overall accuracy level of the assessment of 92%.

Data fusion approaches are also being employed to produce spatially exhaustive, or wall-to-wall, estimates and maps of forest cover clearing within the humid tropics. In the Congo Basin, MODIS and Landsat data are used to create time-series multi-spectral composites, forest area, and forest cover change maps of the entire basin at the Landsat scale for the years 2000, 2005, and 2010. MODIS data are used to radiometrically normalize Landsat data, which are then related to training sites using supervised classification algorithms. This approach, which is currently being applied pan-tropically, is presented in Chapter 8.

Brazil has been measuring deforestation rates in Brazilian Amazonia since the 1980s. The Brazilian National Space Agency (INPE) produces annual estimates of deforestation in the Legal Amazon using a comprehensive annual national monitoring program called PRODES. Spatially explicit results of the analysis of the satellite imagery are published every year (http://www.obt.inpe.br/prodes/). The PRODES project has been producing the annual rate of gross deforestation since 1988 using a minimum mapping (change detection) unit of 6.25 ha, with the release of estimates foreseen around the end of each year. This approach is presented in Chapter 9.

Selective logging and small-scale forest clearing in heterogeneous landscapes require data with moderate-to-fine spatial resolution, more complex computer algorithms capable of detecting less pronounced differences in spectral reflectance, and greater involvement of an interpreter for visual analysis and verification. Methods have been developed and applied for regional mapping of vegetation type and condition (forest cover, deforestation, degradation, regrowth) using Landsat imagery in annual time steps in the Amazon basin. A review of methods for the monitoring of forest degradation is made in Chapter 10.

Chapter 11 describes the development of two recently released high-resolution pan-European forest maps produced for the years 2000 and 2006. The underlying satellite and auxiliary datasets are presented with an overview of the methodology and the main processing steps that governed their production. Validation, as a most important aspect of applicability, receives special attention, and the outlook highlights some aspects, such as differences arising from “forest use” versus “forest cover” concepts, which are important for prospective users.

The United States relies on its national forest inventory for domestic and international reporting of forest change. The U.S. Forest Inventory and Analysis (FIA) program collects data on a set of over 300,000 plots across the United States. A range of attributes are collected in addition to stand volume, including stand age, species composition, and management practice. Plots are resampled on a 5- to 10-year cycle, depending on the state. While FIA is well suited for estimating national forest statistics, it is not designed to accurately capture local dynamics due to disturbance and other rare events. The desire for consistent, geospatial information on forest disturbance and conversion has invigorated the application of Landsat-type remote sensing technology for forest monitoring in the United States. Recent increases in computing power, coupled with the gradual opening of the Landsat archive for free distribution, have resulted in researchers undertaking increasingly ambitious programs in large-area forest dynamics monitoring. In Chapter 12, several of these efforts are described, focusing on national-scale work in the United States.

Australia has developed a system to account for carbon emissions and removals from the land sector, called the National Carbon Accounting System (NCAS). A key component of this system is to track areas of land use change. The NCAS Land Cover Change Program (NCAS-LCCP) produces fine-scale continental mapping and monitors the extent and change in vegetation cover using Landsat satellite imagery from 1972 to 2011 and continues on an annual update cycle, making it one of the most intensive land cover monitoring programs of its kind in the world. The approach is described in Chapter 13.

A forest fire monitoring information system (FIRMS) has been developed for the Russian territory by the Russian Academy of Sciences and is run by the Forest Fire Protection Service of the Federal Forest Agency since the year 2003. The system covers the entire territory of Russia and provides daily information on burned areas in support to fire management activities and fire impact assessments. Satellite remote sensing technology is the main source of data in the system, in particular data from Terra-MODIS and Landsat-TM/ETM+ sensors acquired since the year 2000. Three different burnt area products are generated: at 1 km resolution, at 250 m resolution, and at about 30 m resolution.

3.8 Forest Monitoring with Radar Imagery

Optical mid-resolution data have historically been the primary tool for forest monitoring. However, SAR provides opportunities for forest mapping and monitoring, not least because data can be acquired regardless of sun illumination and weather conditions, which is particularly relevant in the tropics where cloud cover, smoke and haze are prevalent. Through empirical relationships with SAR data or more complex algorithms based on polarimetry or interferometry, the three-dimensional structure of forests can be retrieved, particularly as transmitted microwaves of different frequency and polarization penetrate through and interact with components of the forest volume (e.g., leaves, branches, and/or trunks) and the underlying surface. Changes in vegetation cover and structure over time can also be detected and linked with the processes of deforestation, degradation, or regeneration. Despite the potential of SAR, users are still comparatively few because of the challenges in interpreting, processing, and analyzing radar data and until recently, the limited availability of consistent radar data at regional to global levels. SAR-operating space agencies are, however, beginning to acknowledge the data problem and, following the example of the global systematic acquisition strategy implemented for the Advanced Land Observing Satellite (ALOS) Phased Arrayed L-band SAR (PALSAR) through the Kyoto and Carbon (K&C) Initiative, are making efforts to ensure regular and systematic acquisitions over large regions as part of forthcoming satellite missions. Whilst SAR data are unlikely to fully replace optical sensors in forest monitoring activities, they provide a useful complementary, supplementary or additional resource for monitoring activities. A background to SAR and examples of its use for forest monitoring are provided in Chapter 15.

3.9 Use of Fine Spatial Resolution Imagery for Accuracy Assessment

Whether through wall-to-wall or sample-based approaches, key requirements lie in verification that the methods are reproducible, provide consistent results when applied at different times, and meet standards for assessment of accuracy. Ground reference data (or information derived from very fine spatial resolution imagery that can be considered as being surrogate to ground reference data) are generally recommended as the most appropriate data to assess the accuracy of forest cover change estimation, although their imperfections may introduce biases into estimators of change. Reporting the overall accuracy (i.e., not only the statistical accuracy usually called precision, but also the interpretation accuracy) is an essential component of a monitoring system. Interpretation accuracies of 80%–95% are achievable for monitoring changes in forest cover with moderate-resolution imagery when using only two classes: forest and nonforest. Interpretation accuracies can be assessed through *in situ* observations or analysis of very fine-resolution airborne or satellite data. While it is difficult to verify change from one time to another on the ground unless the same location is visited at two different time periods, a time series of fine- (to very fine) resolution data can be used to assess the accuracy of forest cover change maps.

A new challenge is to provide a consistent coverage of fine-resolution satellite imagery for global forest cover monitoring, i.e., at least a statistical sample or, more challenging, a wall-to-wall coverage. Current plans for the Landsat Data Continuity Mission, the launch of which is scheduled for early 2013, and the European Sentinel-2, scheduled for mid-2014, will both adopt global data acquisition strategies and both (at least at the time of writing) will allow free and open access to their data. The finer resolution (from 1 m × 1 m up to 10 m × 10 m) can be expected to facilitate the derivation of more precise forest area estimates and canopy cover assessment and therefore more reliable statistical information on forest area changes, in particular, for estimating forest degradation and forest regrowth.

About the Contributors

Frédéric Achard is a senior scientist at the Joint Research Centre (JRC), Ispra, Italy. He first worked on optical remote sensing at the Institute for the International Vegetation Map (CNRS/University) in Toulouse, France. Having joined the JRC in 1992, he started his research activities over Southeast Asia in the framework of the TREES project. His current research interests include the development of earth observation techniques for global and regional forest monitoring, and the assessment of the implications of forest cover changes in the tropics and boreal Eurasia on the global carbon budget. Achard received his PhD in tropical ecology and remote sensing from Toulouse University, France, in 1989. He has coauthored over 48 scientific peer-reviewed papers in leading scientific journals including *Nature*, *Science*, *International Journal of Remote Sensing*, *Forest Ecology and Management*, *Global Biogeochemical Cycles*, and *Remote Sensing of Environment*.

Matthew C. Hansen is a remote sensing scientist with research specialization in large-area land cover and land use change mapping. Hansen's research is focused on developing improved algorithms, data inputs, and thematic outputs that enable the mapping of land cover change at regional, continental, and global scales. Such maps enable better informed approaches to natural resource management, including deforestation and biodiversity monitoring and can also be used by other scientists as inputs to carbon, climate, and hydrological modeling studies. Hansen is currently an associate team member of NASA's MODIS Land Science Team, responsible for the algorithmic development and product delivery of time-series maps of global forest cover, croplands, and other vegetation cover types. He also works on mapping deforestation within the Congo Basin as part of the Central Africa Regional Program for the Environment, a USAID-funded project and in Indonesia as part of the Indonesia–Australia Forest Carbon Partnership. Other current research includes improving global cropland monitoring capabilities for the Foreign Agriculture Service of the USDA. Hansen entered the field of remote sensing after serving with the Peace Corps in Zaire and has a PhD in geography from the University of Maryland, College Park, Maryland, an MA in geography, an MSE in civil engineering from the University of North Carolina at Charlotte, North Carolina, and a BEE in electrical engineering from Auburn University, Auburn, Alabama.

References

Achard, F. et al., Estimating tropical deforestation. *Carbon Management*, 1, 271, 2010.

Arino, O. et al., The most detailed portrait of Earth. *European Space Agency Bulletin*, 136, 24, 2008.

Bartholomé, E. and Belward, A.S., GLC2000: A new approach to global land cover mapping from earth observation data. *International Journal of Remote Sensing*, 26, 1959, 2005.

Friedl, M.A. et al., MODIS Collection 5 global land cover: Algorithm refinements and characterization of new datasets. *Remote Sensing of Environment*, 114, 168, 2010.

FSI, *India State of Forest Report 2011*. Forest Survey of India, Ministry of Environment and Forest, Dehra Dun, India, 2011. Available at http://www.fsi.nic.in/. Accessed June 29, 2012.

Hansen, M.C. et al., Estimation of tree cover using MODIS data at global, continental and regional/local scales. *International Journal of Remote Sensing*, 26, 4359, 2005.

Hansen, M.C. et al., Humid tropical forest clearing from 2000 to 2005 quantified by using multitemporal and multiresolution remotely sensed data. *Proceedings of the National Academy of Sciences of the United States of America*, 105, 9439, 2008.

Hansen, M.C. et al., Quantification of global gross forest cover loss. *Proceedings of the National Academy of Sciences of the United States of America*, 107, 8650, 2010.

Herold, M. et al., A joint initiative for harmonization and validation of land cover datasets. *IEEE Transactions on GeoScience and Remote Sensing*, 44, 1719, 2006.

Lepers, E. et al., A synthesis of information on rapid land-cover change for the period 1981–2000. *Bioscience*, 55, 115, 2005.

4

Global Data Availability from U.S. Satellites: Landsat and MODIS

Thomas R. Loveland
Earth Resources Observation and Science Center

Matthew C. Hansen
University of Maryland

CONTENTS

4.1 Introduction

All land remote sensing data from the U.S. government earth observation missions are available to anyone worldwide on a nondiscriminatory basis. U.S. missions are global in scope and emphasis and follow practices that ensure systematic data acquisition, archiving, and accessibility. This chapter focuses solely on data from two U.S. government earth observation missions commonly used for global land studies: the Moderate Resolution Imaging Spectroradiometer (MODIS) and Landsat sensors. Another U.S. mission used for earlier global investigations, the Advanced Very High-Resolution Radiometer (AVHRR) from National Oceanic and Atmospheric Administration (NOAA) polar orbiters, will not be addressed since the end of the AVHRR era is imminent. The follow-on to AVHRR, the Visible Infrared Imager Radiometer Suite (VIIRS) instrument, is a new earth observation data source launched in late 2011 that will build on the MODIS and AVHRR data processing and dissemination models (Justice et al. 2010).

Acquisition practices determine the amount and extent of global imagery available to users. For most U.S. earth observation programs, systematic global collection strategies ensure the availability of imagery over time and space. NASA, NOAA, and the U.S. Geological Survey (USGS) earth observation missions all systematically acquire global data. The NOAA's AVHRR and NASA's MODIS acquire complete global coverage on a daily basis, and the USGS Landsat mission uses the long-term acquisition plan (LTAP) to guide the collection of global seasonal coverage (Arvidson et al. 2006).

However, data can be available yet not practically accessible. If data query and access tools associated with archived data sets are inadequate, efficient access to data may be cumbersome and reduce data use. Perhaps more significant for global studies is data policy. U.S. earth observation policy has long had unrestricted access to imagery. NASA and NOAA have historically stressed free and open access to archives, while the USGS followed a "cost of filling user request" (COFUR) policy and charged per image fees. The cost of those fees has varied over the 40-year history of Landsat, with per scene charges for electronic data ranging from a low of $200 per scene to a high of $4400 per scene. For studies spanning long temporal periods and/or large geographic areas, the cost of Landsat data was too often prohibitive. For Landsat, the cost of scenes made global land mapping applications effectively prohibitive for most researchers and organizations. Recognizing this limitation, the USGS, with NASA support, changed the Landsat data policy in late 2008, and now all Landsat data are available at no cost to any user (Woodcock et al. 2008).

For an earth observation system to enable large-area land cover characterization and monitoring, it must meet certain data requirements. These requirements include (1) systematic global acquisitions, (2) available at low or no cost, (3) with easy access, and (4) featuring geometric and/or radiometric preprocessing. AVHRR data were the first such data sets processed to this standard, for example, the Pathfinder (James and Kalluri 1994) and global inventory monitoring and modeling studies (GIMMS) data sets (Los et al. 1994). The MODIS has advanced this concept through the use of a land science team to develop, implement, and iterate standard image products (Justice et al. 2010). Data from other coarse spatial resolution sensors such as SPOT VEGETATION also meet the criteria outlined above (Maisongrande et al. 2004). For moderate spatial resolution satellite data sets such as Landsat, progress in achieving a data policy and processing system that fulfills these requirements has been more problematic. Future advancement of the earth observation science community will largely depend on applying the experiences developed with coarse spatial resolution data sets to those at moderate spatial resolution. Recent developments with Landsat indicate a promising future for global moderate-resolution data set availability.

4.2 Changing Medium-Resolution Data Policies to Enable Global Studies

The first freely available global coverage of medium spatial resolution imagery was processed by Earth Satellite Corporation as the GeoCover data set (Tucker et al. 2004) and more recently augmented and reprocessed by NASA and the USGS as the global land survey (GLS) data set (Gutman et al. 2008). GeoCover data were first distributed by the Global Land Cover Facility at the University of Maryland (http://glcf.umd.edu/) and the USGS, and download volumes demonstrated the high interest in and demand for free moderate spatial resolution data over large areas. The GLS data sets currently consist of single-best growing season images for decadal and middecadal epochs (1990, 2000, 2005, 2010) and have been used in a host of large-area mapping projects (Hansen et al. 2010; Huang et al. 2008; Masek et al. 2008).

In the mid-2000s, Brazil's Instituto Nacional de Pesquisas Espaciais (INPE) furthered the medium-resolution free data revolution by announcing that all Brazilian Landsat-class imagery would be available at no cost. This was the first official government data policy to institute a no-cost provision of medium spatial resolution data. The USGS followed suit, and since then, other providers are moving to more open pricing models (e.g., the European Space Agency for Sentinel-2). The Committee on Earth Observations Satellites (CEOS) recently established a data democracy initiative that is working toward improving access to earth observations and expanding their use through no-cost access to data, improved data dissemination, provision of affordable software and other analysis tools, and capacity building.

The 2008 decision by the USGS to make U.S. held Landsat data available to anyone at no cost serves as an example of the impact of a free and open data policy (Loveland and Dwyer in press; Wulder et al. in press). Late that year, the USGS announced the end of the Landsat data purchase era and the beginning of "Web-enabled" access to the USGS Landsat archive. Web-enabling was a euphemism for making all data available at no cost over the Internet. In addition to making data available at no cost, the USGS also began providing Landsat data in an orthorectified format. As a result, users now receive application-ready imagery processed to a single format—Level 1 Terrain (L1T). These changes immediately improved the cost-effectiveness and efficiency of most Landsat applications. Additionally, the long-established and studied radiometric calibration of Landsat (Chander et al. 2009) ensures consistent spectral response across space and through time.

The response to the Landsat policy change has been significant. Prior to the policy change, annual Landsat data sales peaked in 2001 when approximately 23,000 products were sold. In the first full year that Landsat data were free, more than 1.1 million images were distributed, and the following year, the number of scenes more than doubled to 2.4 million images and continues to rise. Users in more than 180 countries download Landsat data annually. Also noteworthy is that the demand for data from the historical archive increased significantly in addition to the demand for newer data. Considering the Landsat 7 ETM+ collection, prior to the free-data era, users had accessed approximately 7% of the ETM+ archive. Now, more than 65% of the archive has been used.

The new data policy truly revolutionized the use of Landsat data for education, research, and applications, which therefore increased societal benefits of the 40-year Landsat archive. With the USGS decision in late-2008 to make Landsat data available at no cost to users, all major sources of land remote sensing data from U.S. government programs are also free. There are significant signs that other earth observation data providers are moving toward more open, no-cost data policies.

4.3 MODIS Data

Since before its launch, MODIS has had a land science team tasked with generating data sets that meet the requirements of global land monitoring (Justice et al. 1998, 2002). The MODIS land science team is funded by NASA to develop and maintain the science algorithms and processing software used to generate the MODIS land products and is responsible for coordinating, developing, and undertaking protocols to evaluate product performance, both on a systematic basis through quality assessment activities and on a periodic basis through validation campaigns (Masuoka et al. 2010). The MODIS land products are generated in a gridded format with standard geometric and radiometric corrections and per-pixel quality information (Masuoka et al. 2010; Roy et al. 2002; Vermote et al. 2002; Wolfe et al. 1998). The MODIS archive is systematically reprocessed as new and improved versions of core land processing algorithms are developed.

MODIS products, constituting a 13-year record, are available online at discipline-specific data centers within the NASA Earth Observing System Data and Information System (EOSDIS). Portals for searching and downloading MODIS land products can be accessed via the Land Processes Distributed Active Archive Center (LP DAAC) (https://lpdaac.usgs.gov/). The products are also available through science team–led portals. Looking forward, the experience and lessons learned from MODIS processing and delivery will be a model for global processing of moderate spatial resolution data.

4.4 Landsat Data

The USGS at the Earth Resources Observation and Science (EROS) Center manages the global Landsat archive. EROS has been the steward of the Landsat archive since the first Landsat was launched in July 1972. The EROS archive currently includes over 3 million images with approximately 300 new Landsat ETM+ scenes added to the archive every day. The LTAP described previously is ensuring that seasonal global coverage is systematically acquired and added to the Landsat archive. If Landsat 7 continues to acquire data until its fuel-based end-of-life in 2017, and when the Landsat Data Continuity Mission (LDCM) begins collecting its planned 400 daily global images in January 2013 (Irons et al. in press), 700 Landsat images per day will be added to the archive. This should improve the role of Landsat for global investigations.

The depth of historical global Landsat coverage varies over the 40-year history of the program due to both technical and policy factors. For example, the commercialization of Landsat in the 1980s and 1990s resulted in a reduction of global acquisitions, and the loss of Landsat 5 data relay capabilities restricted TM acquisitions to regions with direct reception ground stations. In addition, a significant portion of global Landsat coverage resides in archives controlled by Landsat International Cooperators (ICs). Approximately 5 million Landsat scenes are estimated to be in international archives maintained by the ICs, and perhaps as many as 3 million of these scenes are unique and not duplicated in the EROS Landsat archive. The IC Landsat collections add significant historical depth and breadth for global studies—if the global science and applications user community has access (Loveland and Irons 2007). The USGS is working closely with the ICs to consolidate as much of these historical holdings as possible into the EROS Landsat archive. Most ICs recognize the value of this initiative and are strong participants.

All new and archived USGS EROS Landsat data are available to anyone at no cost. In order to provide data for free, EROS simplified and automated Landsat product-generation capabilities and data specifications. Using the modular Landsat product-generation system (LPGS), when new Landsat 7 data are received and archived at EROS, an automated cloud cover assessment algorithm computes the percentage of cloud cover for each scene as an attribute for inventory metadata. Scenes that are acquired with less than 60% cloud cover are immediately processed to generate L1T products. The processed L1T data are temporarily available in a disk cache for immediate download for approximately 90 days before new additions cause the older images to "roll off" the disk. However, all 3 million images in the EROS archive, regardless of cloud cover, are available "on demand." In cases where the needed data are not immediately available, an on-demand processing request can be submitted and when the data have been processed, an e-mail is sent to the requestor with a universal resource locator from which to retrieve the data. The current processing capacity of LPGS is approximately 3,500 scenes per day, although as many as 9,000 scenes have been processed in a single day. The LPGS will continue to evolve and improve data processing and access as resources allow.

Landsat L1T data sets provide consistent, orthorectified, and calibrated Landsat scenes for users. All EROS Landsat data are calibrated to a common radiometric standard, instrument performance is constantly monitored, and scenes are orthorectified to a consistent global set of ground control points (Table 4.1).

Access to both processed and archived Landsat data is available primarily through the EarthExplorer and Global Visualization Viewer (GloVis) interfaces, both of which can be used to search and query the archive. In addition to USGS Landsat holdings, the series of Landsat satellites have also collected scenes for locations outside the United States that are not archived or distributed by the USGS EROS Center (see Figure 4.1 for a map of active Landsat ground stations). Landsat ICs also have unique archives containing data that are not duplicated in the EROS archive. Landsat scenes from the IC ground stations must be ordered directly from the specific station that acquired the data. Data prices, formats, and/or processing options may vary according

TABLE 4.1

Landsat L1T Product Specifications

Product type	Systematic or precision terrain correction pending availability of ground control points
Pixel size	30 m (TM, ETM+), 60 m (MSS)
Map projection	Universal transverse mercator
Datum	WGS84
Orientation	North-up
Resampling method	Cubic convolution
Output format	GeoTIFF
Geometric accuracy	~30 m RMSE (United States), ~50 m RMSE (Global)

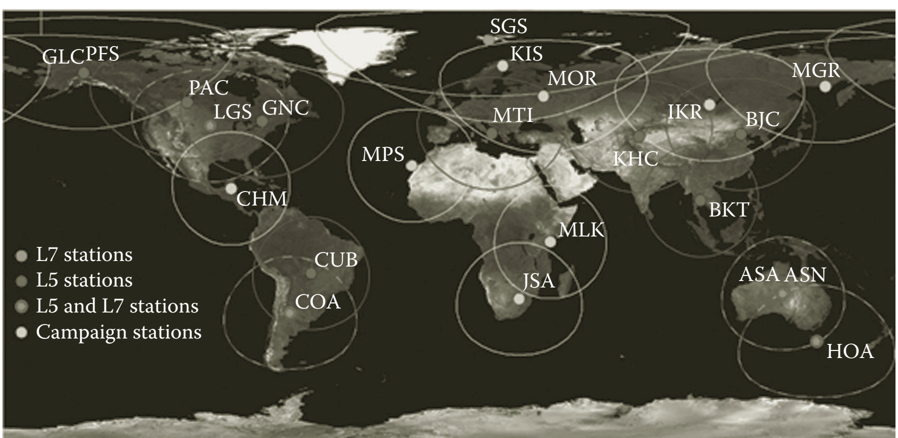


FIGURE 4.1
(See color insert.) Active Landsat ground stations. (More details are available at http://landsat.usgs.gov/about_ground_stations.php.)

to the data provider. A complete list of ground stations and Web addresses for accessing their Landsat collections is available at http://landsat.usgs.gov/about_ground_stations.php.

4.5 Accessing Data

There are a number of interfaces available for accessing MODIS and Landsat data. The GloVis is an intuitive, graphical-based tool for satellite and other image data products with access to several EROS data collections (http://glovis.usgs.gov). Through a graphical map display, any area of interest can be selected, and all available graphical images matching search criteria can immediately be viewed. For Landsat data, it is also possible to navigate to adjacent scene locations in order to identify additional compatible coverage. Controllable criteria include cloud cover limits, date limits, user-specified map layer displays, scene list maintenance, and access to metadata. An ordering interface allows the no-cost download of selected images.

EarthExplorer provides online search, graphical display, data download, and exports of metadata to support users with access to the broader collection of Earth science data sets within the EROS archive. It is a more complex and traditional query tool in comparison to GloVis. However, it offers a number of additional capabilities including:

- Map viewer for viewing overlay footprints and graphical overlays
- Data access tool to search and discover data
- Textual query capability
- Keyhole markup language (KML) export capability to interface with Google Earth
- Save or export queries, results, and map overlay for reuse
- User authentication service for access to specialized data sets and tools

A new tool named Reverb is now in operation and is planned as the "next generation Earth science discovery tool," providing a means for discovering, accessing, and invoking NASA data products and services (http://reverb.echo.nasa.gov). Searches can query by platform, instrument and sensor, or specific campaign and can be refined spatially, temporally, or by processing level and product type. Reverb is recommended for accessing MODIS data. There is considerable cross-fertilization between the various search systems. For example, Reverb can also serve as an interface to other archives, including those of Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) and AVHRR.

4.6 Conclusion

U.S. earth observation initiatives are now consistently committed and managed for use in global land studies. Especially critical are the use of systematic global acquisition strategies and nondiscriminatory, no-cost access to the acquired data. Continuation of these practices and the timely launch of follow-on missions are essential next steps in ensuring that current investments in global land studies are continued into the future. The launch of LDCM potentially extends the Landsat record for another 5–10 years (until 2018–2023), but after that no follow-on capability is currently authorized. On the other hand, the MODIS record is currently transitioning to the VIIRS era as this next generation of NOAA polar orbiters becomes operational. An operational moderate spatial resolution land monitoring program has been proposed, the National Land Imaging Program (Office of Science and Technology Policy 2007), but no substantive investment made to date for its implementation.

As moderate spatial resolution data policies and processing mimic those of coarser resolution data, new science capabilities will be enabled. The next few years are quite possibly going to be Landsat's "golden years," the time in which the Landsat program achieves its full potential for global studies. Free Landsat data, the consolidation of international holdings into the EROS archive, the expanded availability of these data in a consistently processed format, and new global coverage from Landsat 7 and the LDCM are enabling and improving the use of Landsat for global studies. Innovative improvements in Landsat data products and delivery systems, such as the Web-Enabled Landsat Data (WELD) system developed by Roy et al. (2010), will serve as catalysts for improved global use of Landsat. The integrated use of systematically acquired multiresolution, multitemporal, multispectral global data sets, such as MODIS and Landsat, will become a standard scientific practice.

About the Contributors

Thomas Loveland is a senior research scientist with the U.S. Geological Survey EROS Center in Sioux Falls, South Dakota. He has a BS and MS in geography from South Dakota State University, Brookings, South Dakota, and a PhD in geography from the University of California, Santa Barbara, California. Loveland currently coleads the USGS–NASA Landsat Science Team and is engaged in research in the use of remote sensing for land cover studies spanning local to global scales.

Matthew C. Hansen is a professor in the Department of Geographical Sciences at the University of Maryland, College Park, Maryland. He has a bachelor of electrical engineering from Auburn University, Auburn, Alabama. His graduate degrees include a master of engineering in civil engineering and a master of arts in geography from the University of North Carolina at Charlotte, North Carolina, and a doctoral degree in geography from the University of Maryland, College Park, Maryland. His research specialization is in large-area land cover monitoring using multispectral, multitemporal, and multiresolution remotely sensed data sets. He is an associate member of the MODIS Land Science Team and a member of the GOFC-GOLD Implementation Working Group.

References

Arvidson, T., et al., The Landsat-7 Long-Term Acquisition Plan: Development and validation. *Photogrammetric Engineering and Remote Sensing*, 72, 1137, 2006.

Chander, G., Markham, B.L., and Helder, D.L., Summary of current radiometric calibration coefficients for Landsat MSS, TM, and EO-1 ALI sensors. *Remote Sensing of Environment*, 113, 893, 2009.

Gutman, G., et al., Towards monitoring land-cover and land-use changes at a global scale: The global land survey 2005. *Photogrammetric Engineering and Remote Sensing*, 74, 6, 2008.

Hansen, M.C., Stehman, S.V., and Potapov, P.V., Quantification of global gross forest cover loss, *Proceedings of the National Academy of Sciences*, 107, 8650, 2010.

Huang, C., et al., Assessment of Paraguay's forest cover change using Landsat observations. *Remote Sensing of Environment*, 67, 1, 2008.

Irons, J.R., Dwyer, J.L., and Barsi, J.A., The next Landsat satellite: The Landsat Data Continuity Mission. *Remote Sensing of Environment*, in press (http://dx.doi.org/10.1016/j.rse.2011.08.026).

James, M.E. and Kalluri, S.N.V., The Pathfinder AVHRR land data set: An improved coarse resolution data set for terrestrial monitoring. *International Journal of Remote Sensing*, 15, 3347, 1994.

Justice, C.O., et al., The Moderate Resolution Imaging Spectroradiometer (MODIS): Land remote sensing for global change research. *IEEE Transactions on Geoscience and Remote Sensing*, 36, 1228, 1998.

Justice, C.O., et al., An overview of MODIS Land data processing and product status. *Remote Sensing of Environment*, 83, 3, 2002.

Justice C.O., et al., The evolution of U.S. moderate resolution optical land remote sensing from AVHRR to VIIRS. In B. Ramachandran, C.O. Justice, and M.J. Abrams (Eds.), *Land Remote Sensing and Global Environmental Change: NASA's EOS and the Science of ASTER and MODIS*. New York: Springer, 2010.

Los, S.O., Justice, C.O., and Tucker, C.J., A global 1° by 1° NDVI data set for climate studies derived from the GIMMS continental NDVI data. *International Journal of Remote Sensing*, 15, 3493, 1994.

Loveland, T.R. and Dwyer, J.L., Landsat—building a strong future. *Remote Sensing of Environment*, in press (http://dx.doi.org/10.1016/j.rse.2011.09.022).

Loveland, T.R. and Irons, J.R., Landsat Science Team meeting summary. *The Earth Observer*, 19, 10, 2007.

Maisongrande, P., Duchemin, B., and Dedieu, G., VEGETATION/SPOT: An operational mission for the Earth monitoring; presentation of new standard products. *International Journal of Remote Sensing*, 25, 9, 2004.

Masek, J., et al., North American forest disturbance mapped from a decadal Landsat record. *Remote Sensing of Environment*, 112, 2914, 2008.

Masuoka, E., et al., MODIS land data products: generation, quality assurance and validation. In B. Ramachandran, C. Justice, and M. Abrams (Eds.), *Land Remote Sensing and Global Environmental Change: NASA's EOS and the Science of ASTER and MODIS*. New York: Springer, 2010.

Office of Science and Technology Policy, *A Plan for a National Land Imaging Program*, Future of Land Imaging Interagency Working Group, August, 2007.

Roy, D.P., Borak, J.S., Devadiga, S., Wolfe, R.E., Zheng, M., and Descloitre, J., The MODIS land product quality assessment approach. *Remote Sensing of Environment*, 83, 62, 2002.

Roy, D.P., et al., Web-enabled Landsat Data (WELD): Landsat ETM+ composited mosaics of the conterminous United States. *Remote Sensing of Environment*, 114, 35, 2010.

Tucker, C.J., Grant, D.M., and Dykstra, J.D., NASA's global orthorectified Landsat data set. *Photogrammetric Engineering and Remote Sensing*, 70, 3131, 2004.

Vermote, E.F., El Saleous, N.Z., and Justice, C.O., Atmospheric correction of MODIS data in the visible to middle infrared: First results. *Remote Sensing of Environment*, 83, 97, 2002.

Wolfe, R.E., Roy, D.P., and Vermote, E.F., MODIS land data storage, gridding, and compositing methodology: Level 2 grid. *IEEE Transactions on Geoscience and Remote Sensing*, 36, 1324, 1998.

Woodcock, C., et al., Free access to Landsat imagery, *Science*, 320, 1011, 2008.

Wulder, M.A., et al., Opening the archive—how free data has enabled the science and monitoring promise of Landsat. *Remote Sensing of Environment*, in press (http://dx.doi.org/10.1016/j.rse.2012.01.010).

5

Sampling Strategies for Forest Monitoring from Global to National Levels

Stephen V. Stehman
State University of New York

CONTENTS

5.1 Introduction

Remote sensing plays a key role in forest monitoring because it offers a cost-effective option for frequent observation of vast areas of forest. Forest attribute maps derived from remote sensing may be integrated with forest inventory data in a variety of ways within a forest monitoring framework (Corona 2010). The effective use of remote sensing to produce maps of forest attributes has been described and convincingly demonstrated elsewhere in this book. These maps serve the critical purpose of providing spatially explicit information for forest attributes. The focus of this chapter is not on monitoring forests by complete coverage mapping but on taking advantage of remote sensing via a sampling approach to forest monitoring. Whereas it is sometimes too costly and time consuming to obtain wall-to-wall coverage using the quality of imagery and processing desired for a particular forest monitoring objective, sampling provides the opportunity to apply measurement and observation protocols to a much smaller total area, and this may allow for the use of very high-resolution imagery or sophisticated classification methods that otherwise would not be practical for a complete coverage assessment. A sampling-based monitoring framework targets aggregate properties such as the total area of forest and the area of forest cover change. A traditional intensive ground-based forest inventory approach to forest monitoring is another option based on sampling. But in this chapter, remotely sensed data, defined as data from sensors placed on aircraft or space-based platforms, are assumed to be the basis for forest monitoring.

Forest monitoring can be applied to a variety of forest characteristics, for example forest cover and biomass. In this chapter, the focus will be on monitoring forest cover. The attention to forest cover allows for framing the monitoring objective as an area estimation problem, an objective commonly addressed in mapping applications using remotely sensed data (Gallego 2004). Area estimation can be approached in two ways. One approach is to compute area from a complete coverage map of the target region, for example, using a complete coverage map of deforestation to compute the area deforested. Mayaux et al. (2005, 374–375) review applications in which global land cover and forest mapping efforts are used as the basis for estimating the area of deforestation. The other approach is to estimate the area of deforestation from a sample. By requiring information on a smaller subarea of the full region, sampling offers advantages of significant cost reduction (e.g., fewer satellite images or fewer people to interpret aerial photographs) and better accuracy of the measurements of area. Mayaux et al. (1998) critique the limitations and practical advantages of the two approaches. A further advantage of remote sensing is that it offers an option for forest monitoring based on a consistent methodology that can allow for more direct regional comparisons, for example, of regional rates of forest change than is possible when methods used for monitoring vary by region. Hansen et al. (2010) and the FRA 2010 remote sensing survey (Ridder 2007; FAO 2009) are examples in which regional comparisons have been facilitated because regionally consistent sampling and analysis protocols have been applied to remote sensing assessments of forest change.

The area estimation objective highlights a distinction between two common uses of maps constructed from satellite imagery. The spatially explicit information of pattern and location conveyed by a map is critical to some applications, whereas in other applications, information aggregated over a specified region is sufficient. The latter applications address aggregate properties such as totals, means, or proportions, for example, area of forest cover, proportion of area of deforestation, or total biomass. These aggregate properties or population parameters can be estimated from a sample. When the objective is to estimate area, a statistical comparison between the mapping and sampling approaches can be framed in terms of accuracy and precision. Is the map sufficiently accurate to provide valid change estimates (i.e., bias attributable to classification error is negligible)? Is the sample-based estimate sufficiently precise to provide useful change estimates (i.e., sampling variability is small relative to the quantity being estimated)? Stehman (2005) provides guidance for evaluating the trade-off between precision (sampling variability) and accuracy (measurement or interpretation error) for estimating area.

Sample-based forest monitoring using remotely sensed data has been successfully implemented to provide estimates of forest cover and forest cover change over the tropics (e.g., Achard et al. 2002) and global forest biomes (e.g., Hansen et al. 2010). The global Forest Resources Assessment (FRA) remote sensing survey (FAO 2009) is another recent application of a sample-based forest monitoring activity. These successful operational monitoring efforts are the outcome of years of research and development probing the question of how large-area forest monitoring can be accomplished with the aid of remote sensing. The basic theory and methods underlying the sampling approach to forest monitoring are reviewed in this chapter. Although much progress has been made developing appropriate sampling methods, additional work is needed to further refine and understand the methods of current practice and to develop new methods for more cost-efficient and accurate forest monitoring using remotely sensed data. The prospects for sample-based forest monitoring in the future are discussed in the closing section of this chapter.

5.2 Fundamental Sampling Concepts and Methods

In this section, basic concepts and methods of sampling are defined to establish the context for sample-based forest monitoring. The approach described takes a finite population sampling perspective in which the region of interest (e.g., a country, a continent, or the forested biomes of earth) is partitioned into a set of N nonoverlapping elements or spatial units (e.g., 5 km × 5 km units) called the *universe*. For each element of the universe, one or more attributes or measurements may be obtained (e.g., area of forest cover or area of forest degradation for each unit). A *population* will refer to a collection of these measurements for all N units of the universe, and a *parameter* is defined as a number that describes an aggregate property of this population (e.g., total area of forest cover, or percent loss of forest cover). A *sample* is a subset of the N elements of the universe, and a sample therefore consists of one or more such elements.

Although landscapes are truly continuous, the finite population perspective usually provides a close approximation to reality. For example, if the objective is to obtain the total area of forest for a region, dividing the area into 5 km × 5 km units and summing the forest area over all N such units in the region will yield the same total area as a measurement of area from the unpartitioned (full) region. Some forest characteristics may be less amenable to a sampling approach; for example, certain landscape pattern metrics such as contiguity of patches or landscape diversity may not be estimated well via a sampling approach (Hassett et al. 2012). But for estimating area and change in area, the finite population sampling perspective provides a frequently used, familiar approach that is simple, practical, flexible, and effective.

A *sampling strategy* consists of three major components: the sampling design, response design, and analysis. The sampling design is the protocol by which a subset of the universe (i.e., the sample) is selected. For example, the subset could be 100 sampling units where each sampling unit is 5 km × 5 km. The response design is the protocol for obtaining the measurements of each sampling unit. For example, the response design for the objective of monitoring area of forest cover would be the protocol implemented to measure the area of forest cover of each unit sampled. The protocol may include specification of the imagery to use, the classification method applied to the imagery, and the definition of forest. The analysis protocol includes the formulas used to estimate parameters of interest and the standard errors associated with these estimates.

5.2.1 Basic Sampling Designs

Once the region to be monitored has been partitioned into N spatial units or elements that constitute the universe, a variety of sampling designs may be considered to select the sample. Choosing a sampling design requires three main decisions: (1) Will stratification be used? (2) Will the sampling unit be a cluster? (3) Will the primary selection protocol be simple random, systematic, or something else? The answers to these three questions will determine the sampling design. Examples of sampling designs created by different combinations of these decisions exist in applications to forest monitoring using remotely sensed data (Section 5.3). Considerations influencing each of these decisions are briefly reviewed.

Stratification is the process of grouping the N elements of the universe into strata such that each element belongs to one and only one stratum. Stratification is generally used for two purposes. If the objectives specify reporting forest characteristics by region (e.g., by continent, country, or provinces within a country), strata may be defined by these reporting regions. Typically, the sampling design is then developed with the goal of allocating the sample such that each stratum has a sufficient sample size to achieve acceptable standard errors for estimates of that stratum. Stratification thus can be used to avoid the problem that a reporting region that occupies a relatively small proportion of the full area monitored will have too few sample units to obtain precise estimates for that region.

Another use of stratification is to define strata to minimize the standard error of an estimate. The optimization is attained by defining strata such that strata means differ from one another and elements within a stratum have similar responses. For example, if the objective is to estimate forest cover loss, the strata could be advantageously defined by the amount of forest cover loss, and strata representing no loss, low loss, moderate loss, and high loss may be defined based on the available information of forest cover loss for each of the N elements. Stratifying for the purpose of improving precision requires that ancillary data related to the response of interest are available. For example, Hansen et al. (2010) used complete coverage, MODIS-derived forest cover loss as ancillary data to define strata related to Landsat-derived gross forest cover loss, where Landsat-derived loss was the target measurement for the assessment.

A cluster is a group of elements of the universe that is sampled as a single entity. For example, the basic element of the universe may be defined as a 1 km × 1 km unit, and a 10 km × 10 km group of 100 such units could be defined as a cluster. A cluster sampling protocol would then be applied to the 10 km × 10 km cluster units, but the data would be collected at the support of the 1 km × 1 km units within a cluster. In the terminology of cluster sampling, the 10 km × 10 km unit is labeled a primary sampling unit (PSU) and the 1 km × 1 km unit is called a secondary sampling unit (SSU).

Cluster sampling may be implemented as either one-stage or two-stage sampling (additional stages are possible but the discussion here will be limited to two stages). The first stage of sampling is always a selection of PSUs. For one-stage cluster sampling, all SSUs within each sampled PSU are observed so only one stage of sampling is used. One-stage cluster sampling is thus very similar to defining an element of the universe based on the PSU. For example, the 10 km × 10 km units (PSUs) could be considered the elements of the universe because the 1 km × 1 km units are always selected in groups of 100 defined by the PSU. The only difference between a sample of 10 km × 10 km units and a one-stage cluster sample of 1 km × 1 km units grouped into sets (PSUs) of 100 is that for the cluster sample, the data would be recorded for each 1 km × 1 km unit within the PSU, whereas this measurement on each 1 km × 1 km unit would likely not be retained if the 10 km × 10 km unit is defined as the element of the universe.

In two-stage cluster sampling, a sample of SSUs is selected within each sampled first-stage PSU. Two-stage cluster sampling is motivated by the recognition that typically units spatially proximate to each other will have relatively similar values, and this spatial correlation of the sample observations will tend to inflate the standard errors of estimates from cluster sampling relative to a more spatially dispersed sample of the same size. So instead of sampling all SSUs within a sampled PSU, a sample of SSUs is selected and the cost and time savings achieved by the lower effort per PSU can be allocated to increase the number of PSUs sampled.

The choice of whether to use clusters is typically driven by cost. When the primary data are obtained from remote sensing, the cost of the imagery and the time required to obtain and process the imagery are key considerations.

For example, if RapidEye imagery is used, the size of the PSU may be defined to be a portion of a RapidEye image so that the number of RapidEye images that must be purchased is limited. Cluster sampling allows control over the spatial distribution of the sample because of the spatial grouping of elements into a fixed number of sampled clusters.

Whether clusters or strata are present, it is necessary to specify a protocol for selecting the elements of the sample. For *simple random* selection of a sample size of n sampling units, the sample is selected such that all possible sets of n units have the same probability of being selected. For example, if the universe is first partitioned into strata and simple random selection is implemented in each stratum, the design is called stratified random sampling. For cluster sampling, the simple random selection protocol could be used to select a first-stage sample of PSUs, or applied within sampled PSUs to select a second-stage sample of SSUs. For a *systematic* selection protocol, a random starting element or location is selected, and the remaining sample elements are selected based on their location in a list of all N elements of the universe or based on their spatial location relative to the random starting location. Systematic selection can also be applied in combination with strata and clusters. For example, if strata are present, the elements sampled within a stratum can be selected via the systematic protocol. Similarly, both stages of two-stage cluster sampling could be implemented via a systematic selection protocol. Some considerations influencing the choice of selection protocol are discussed in Section 5.5.

5.2.2 Inclusion Probabilities and Probability Sampling

A useful general perspective of sampling design is obtained by focusing on *inclusion probabilities*. An inclusion probability is defined as the probability that a particular element of the universe is included in the sample. That is, prior to selecting the actual sample, for a given element of the universe, what is the probability of that element being included in the sample selected? Inclusion probabilities thus inform about the process of sample selection. For simple random sampling of n elements from a universe of N elements, the inclusion probability is n/N for each element. For systematic sampling from a list of N elements, if the sampling interval is K (i.e., select every Kth element after a random selection of the first sample element), the inclusion probability is $1/K$ for each element (see Overton and Stehman 1995 for additional examples).

Inclusion probabilities play an important role in defining a *probability sample*. Specifically, a probability sample is defined by two conditions: (1) the inclusion probabilities for all elements in the sample must be known and (2) the inclusion probabilities for all elements of the universe must be greater than zero. The rationale for these conditions is explained in Overton and Stehman (1995). For this chapter, it suffices to recognize that a probability sampling protocol conveys a degree of statistical rigor to the sample-based estimates and inference. For the basic sampling designs typically used in practice (e.g., simple random sampling, systematic sampling, stratified random sampling, and one-stage and two-stage cluster sampling with either simple random or systematic sampling for each stage), the inclusion probabilities are known and these designs meet the conditions of probability sampling (Särndal et al. 1992). If the sampling design does not follow a standard selection protocol, it is necessary to establish that the protocol meets the conditions defining a probability sample. Some practical, but ad hoc selection protocols may create very challenging problems for defining inclusion probabilities, and for very complex selection protocols the inclusion probabilities may be intractable.

5.2.3 Inference

The process of generalizing from the sample data to describe characteristics of the full population is called inference. Clearly, an understanding of inference is necessary when a sampling approach to forest monitoring is used. The two approaches to inference most frequently used in finite population sampling are design- and model-based inference. The two approaches differ primarily in how uncertainty or variability is represented as determined by the definition of the "variable" in each approach.

In design-based inference, the observations obtained for each element of the population are treated as fixed constants and therefore the response or observation is not considered a variable. The uncertainty in design-based inference is attributable to the randomization determining which elements of the universe are selected for observation. It is variation of the estimate from sample to sample that is the uncertainty of interest in design-based inference, and consequently the sampling design is of paramount importance. Specifically, for a given universe and sampling design, the *sample space* is defined as the set of all possible samples that could be selected by that particular design. For each possible sample from a given population, the estimate of the parameter of interest would differ for different samples. For example, suppose the target parameter is the area of deforestation over a 5-year period. A systematic sample of 10 km × 10 km units is selected by randomly locating a grid, with each grid point separated by 250 km. If the sample is repeated by a second random placement of the grid, the estimate of deforestation is likely to change. In design-based inference, it is the variability of an estimate over all possible samples comprising the sample space that characterizes uncertainty. Because the sampling design determines the sample space, the name "design-based" inference is naturally applied.

For model-based inference, the response observed for each element of the population is viewed as a variable, and inference is conditional on the sample obtained. For example, the values of a finite population $y_1, y_2, \ldots, y_N$ are viewed as realizations of the random variables $Y_1, Y_2, \ldots, Y_N$. The goal is to estimate some function of all the y's in the population, $h(y_1, y_2, \ldots, y_N)$, for example, the mean or total (Valliant et al. 2000, 2). After the sample of n elements has been obtained, estimating $h(y_1, y_2, \ldots, y_N)$ entails predicting a function of the unobserved Y's. A model is used for this purpose. The model typically incorporates an auxiliary variable (denoted x) that is related to Y. The model would then include a specification of how the variable Y is related to x, this relationship being represented by the model M. For example, the model M could be a simple linear relationship between the expected value of Y and x, $E_M(Y_i) = \beta x_i$ $(i = 1, 2, \ldots, N)$, with the covariance between the variables Y_i and Y_j specified as $\text{cov}_M\ (Y_i, Y_j) = \sigma^2 x_i$ if $i = j$ and $\text{cov}_M\ (Y_i, Y_j) = 0$ if $i \neq j$ (Valliant et al. 2000, 4). The model and observed sample data are the basis for predicting the unobserved Y's, so the probability model specified plays a key role in model-based inference. An example applying model-based inference is provided at the end of Section 5.4.

The choice of inference framework impacts sampling design decisions. Design-based inference is predicated on the sampling design being a probability sampling design. Therefore, if design-based inference will be used, only probability sampling designs should be considered. Conversely, model-based inference does not require a probability sample. The model specified for model-based inference may take into account the fact that the sample was obtained via cluster sampling or stratified sampling, but this would represent a model specification choice and not a required dependence of the inference on the sample. However, advocates of model-based inference often cite the potential advantage that randomization provides to avoid accusations that a sample was subjectively chosen to achieve certain outcomes. Model-based inference can be conducted with a probability sample, but design-based inference cannot be conducted unless a probability sampling design has been implemented.

5.2.4 Estimation

Once the sample has been selected and the data obtained, a variety of estimators may be available to estimate a parameter of interest. For probability sampling designs and design-based inference, a general unbiased estimator of a population total is the Horvitz–Thompson estimator. Suppose the observation on element u of the sample is denoted y_u and the inclusion probability for element u is denoted π_u. If Y is the population total (i.e., the sum of y_u over all N elements of the population), the Horvitz–Thompson estimator of Y is

$$\hat{Y} = \sum_{u \in s} y_u / \pi_u \tag{5.1}$$

where the summation is over the elements of the sample. For example, if y_u is the area of deforestation for element u and Y is the total area of deforestation for the region, then Y can be estimated from a probability sample using the Horvitz–Thompson estimator. For the basic sampling designs typically used in practice, the Horvitz–Thompson estimator simplifies to a special case formula. For example, for a simple random sample of n elements, the estimator simplifies to $\hat{Y} \quad N\bar{y}$, where $\bar{y}$ is the sample mean of the response y_u, and for stratified random sampling of n_h elements from the N_h available in stratum h (H strata total), the Horvitz–Thompson estimator simplifies to

$$\hat{Y} = \sum_{h=1}^{H} N_h \bar{y}_h \tag{5.2}$$

where $\bar{y}_h$ is the sample mean in stratum h.

In most applications, it is possible to obtain an auxiliary variable x_u that is associated with the response of interest, y_u. Such an auxiliary variable may be used to advantage to reduce the standard error of the parameter estimate. A widely applicable estimator for this purpose is the generalized regression estimator (GRE) (see Särndal et al. (1992, 225) for full details of this estimator). More familiar simple estimators such as the ratio and regression estimators applied to simple random sampling are special cases of this general form. Because the GRE encompasses a variety of models of the relationship between the response y and one or more auxiliary variables, the GRE is almost always better (i.e., more precise) than the generalized difference estimator (Särndal et al. 1992, section 6.3). The GRE belongs to the class of "model-assisted estimators" (Särndal et al. 1992, 227). These estimators employ a model to information in one or more auxiliary variables to improve precision of estimates, but the estimators are not dependent on the validity of the model, and inference is still design based.

5.2.5 Desirable Design Criteria

Choosing a sampling design for forest monitoring using remote sensing should be guided by the monitoring objectives and by desirable design criteria specified for a particular application. A list of potential desirable criteria follows, but the prioritization of these criteria will be different depending on the specific application.

1. *The sampling protocol satisfies the requirements of a probability sampling design*. As previously stated, this criterion is essential to support design-based inference, but is optional for model-based inference.
2. *The sampling design is easy to implement*. Simplicity of design can be a major virtue. It is critical that the design is implemented correctly, so a simple protocol is advantageous in this regard. Also, a simple design is simpler to analyze, as, for example, when using a model-assisted estimator to improve precision (Section 5.2.4).

3. *The design is cost-effective.* The rationale for this criterion is obvious because a design goal should be to obtain adequately precise estimates (i.e., acceptably small standard errors) for the lowest cost possible. Of course, what constitutes "adequate precision" will be application dependent.
4. *The sample is spatially well distributed* (i.e., spatially balanced). If the sample units are spatially dispersed throughout the target region, the sample has intuitive appeal and often results in smaller standard errors.
5. *The standard errors of estimates resulting from the design are small.* In design-based inference, this would mean that estimates of the target parameter from different samples would be relatively similar.
6. *An unbiased or nearly unbiased estimator of variance is available.* This criterion specifies that standard errors quantifying the uncertainty of the estimates can be provided without undue reliance on approximations other than those related to the need for a large sample size to justify the variance approximation. This criterion becomes particularly relevant when considering the use of systematic sampling because a variance approximation will need to be used as an unbiased estimator of variance is not available for systematic sampling.
7. *A change in sample size can be accommodated before the full sample has been selected.* This criterion is valuable because the final cost of completing the sample data collection is often difficult to predict, so it may be necessary to reduce the sample from the initial target size, or in rare cases it may be possible to increase the sample size. Budgets also sometimes change, and the sample size may need to be reduced or increased accordingly.
8. *The design is transparent and familiar to users of the information.* This criterion may be particularly relevant if nonscientists will be using the monitoring results to inform policy decisions. Transparency may include information of actual plot locations or specific details of how randomization is incorporated into the selection protocol.

5.3 Applications of Sampling to Estimate Forest Cover Change from Remotely Sensed Data

Published studies demonstrating the application of a sampling approach to forest monitoring based on remote sensing are reviewed. The review focuses on two broad categories: actual applications in which forest monitoring based on remotely sensed data has been implemented and evaluative studies in which different sampling design and estimation strategies have been compared. The application studies are discussed first, followed by the design evaluation studies (Section 5.4). The applications are presented in chronological order.

The United Nations Food and Agriculture Organization's (FAO) FRA in 1990 is a landmark application of a sampling approach employing satellite imagery to derive estimates of forest change. The FRA 1990 design used 117 Landsat scenes as the sampling units (FAO 1996). The design was stratified based on three major geographic regions (Africa, Latin America, and Asia) and 10 subregions among the three major regions. The sample size allocated to these regions was based on the expected area of deforestation, as predicted for each subnational unit based on prevalence of forest, human population size, and per capita income. An additional level of stratification (FAO 1996, 8) was based on forest cover in Asia and Latin America (>70%, 40%–70%, and 10%–40%, where cover was derived from country-specific inventories) and on dominant forest types in Africa (forest, woodland, or tree savanna for the three strata). Thus both purposes of stratification were accommodated in this design: stratification for regional reporting and stratification for minimizing standard errors of estimates. Within each sampled Landsat scene, a subsample of points was obtained using a 2 km × 2 km grid. The land cover class was interpreted from Landsat imagery at each sample point of the dot grid to obtain area estimates for each frame or PSU. To assess change in forest cover, the sampling unit was defined as "the overlap area of a pair of multi-date Landsat scenes" (FAO 1996, 7). The FRA 2000 assessment employed the same sample as the FRA 1990, with an additional time period included to estimate change from 1990 to 2000. This design employs a combination of design elements discussed in Section 5.2.1. The sampling design may be labeled as a two-stage cluster sample, with stratified random sampling used at the first stage to select a sample of Landsat scenes (PSUs) and systematic sampling used at the second stage to select points (SSUs).

The TREES II design (Richards et al. 2000) was implemented for estimating deforestation in the humid tropical forests for the time period 1990–1997. This design employed full and quarter Landsat scenes as the sampling units, with $n = 104$ sampled out of a possible $N = 740$ units. The sampling design had five strata based on percent forest cover and percent deforestation within each of the 740 units (Richards et al. 2000, 1480). Gallego's (2005, 370) retrospective assessment of the TREES II design concluded that it was statistically sound but overly complicated. As a simplification of the TREES II design, Gallego (2005) proposed employing stratification to partition variability of change (i.e., low and high variation) and selecting sample locations from a systematic grid. Similar to the TREES II design, the proposed modification is still strongly linked to using Landsat scenes as the basis for defining the sampling unit. The study region would first be partitioned by a tessellation based on Landsat scenes that accounted for scene overlap. The sample units created by this partitioning are unequal in size (area), and Gallego (2005) suggested implementing a design where the units are sampled with probability proportional to their area.

Mayaux et al. (2005) provide a retrospective critique of both the FRA 1990 and TREES II designs. They suggest that stratified sampling based on forest distribution and fragmentation, as determined from coarse-resolution satellite imagery, should be considered (Mayaux et al. 2005, 382). Knowledge of deforestation hot spots should also be used, possibly via stratification, to improve precision. Mayaux et al. (2005) proposed a design for future FRA global assessments, suggesting a large systematic sample of 10 km × 10 km blocks located at the intersections of 1° lines of latitude and longitude. This sample would consist of approximately 10,000 sample units. Such a design represents a shift from the strong dependence on Landsat images of the TREES II and FRA 1990, but as described in Mayaux et al. (2005), it would not incorporate stratification based on the anticipated degree of deforestation.

Hansen et al. (2008) selected a stratified random sample of 18.5 km × 18.5 km units to estimate gross forest cover loss during 2000–2005 in the humid tropical forest biome. The strata were determined based on MODIS-derived forest cover loss for each of the N units, and the estimated gross forest cover loss was quantified using Landsat imagery. A similar stratified design was implemented in the boreal and temperate forest biomes (Potapov et al. 2008) and the dry tropical forest biome (Hansen et al. 2010). The use of a common stratified sampling design and Landsat-derived gross forest cover loss for all four forested biomes is an example of how application of a consistent methodology can facilitate comparisons of rates of change at a global scale (Hansen et al. 2010). Hansen et al. (2008, 2010) employed a regression estimator (Section 5.2.4) to estimate gross forest cover loss, and the reported standard errors from this model-assisted strategy were generally small.

The FRA 2010 remote sensing survey is another example in which the consistency of methodology leads to global comparisons of forest change uncompromised by confounding differences in methods of measuring forest change. The FRA 2010 remote sensing survey is a systematic sample with the sample units (10 km × 10 km blocks) centered at the intersections of 1° lines of latitude and longitude (Ridder 2007; FAO 2009). Duveiller et al. (2008) report results from an intensified FRA sample to estimate forest cover change in Central Africa between 1990 and 2000. The sample grid points were located at every 0.5° intersection of latitude and longitude, yielding a fourfold increase in sample size over the 1° intersection grid. A total of 571 sample blocks (10 km × 10 km) were selected, although cloud cover prevented analysis of some sample blocks. The estimates of forest change had reasonably low standard errors, demonstrating the operational success of the methodology (Duveiller et al. 2008, table 2).

Levy and Milne (2004) review sample-based studies for estimating afforestation and deforestation in Great Britain. The National Countryside Monitoring Scheme (NCMS) of Scottish Natural heritage is a sample of 487 1 km × 1 km plots, with change interpreted from aerial photographs taken in the 1940s and 1980s. The countryside survey is based on 381 plots, also 1 km × 1 km, distributed throughout Great Britain. The countryside survey incorporates stratification based on "underlying environmental characteristics such as climate, geology and physiology" (Fuller et al. 1998, 103).

Leckie et al. (2002) describe a study to report deforestation and its carbon consequences for Canada. The sampling design is linked to the ongoing Canadian National Forest Inventory sample of 2 km × 2 km photoplots centered at points on a 20 km × 20 km grid. Stratification by expected deforestation level is incorporated in the sampling design. In the high deforestation strata, the sampling grid is intensified to 10 km × 10 km to increase the sample size. Interpretation of Landsat imagery is proposed to obtain the deforestation data.

Dymond et al. (2008) employed a stratified sampling design to estimate change in forest area between 1990 and 2002 for a portion of the South Island of New Zealand. The six strata defined were nonforest no change, two-forest no change strata (one for which a spectral difference was noted, the other for which no spectral difference was observed), a forest to nonforest change stratum, a nonforest to forest change stratum, and a "big clumps" stratum that could include to forest or from forest change, with these changes occurring in clumps of 5 ha or more. This "big clumps" stratum was expected to contain most of the change that could be identified from Landsat imagery, so this stratum was exhaustively sampled (censused). For the other five strata, sample points were randomly selected within each stratum. Dymond et al. (2008) found that this stratified design was much more efficient than simple random sampling.

To summarize these application studies, a variety of sampling designs have proven to be effective for monitoring forest change from remotely sensed data. Many of the basic design options described in Section 5.2.1 have been implemented in practice. Most studies employed a spatial sampling unit, with the FRA 1990 design and Dymond et al. (2008) being exceptions for which point sampling was implemented (the FRA 1990 did use a spatial sampling unit at the first stage of the two-stage cluster design). The early use of Landsat scenes or quarter scenes as the sampling units has generally been replaced in favor of smaller spatial units. Stratification is present in the majority of the designs implemented, with the FRA 2010 remote sensing survey being the most notable application not using stratification. Two-stage sampling in which the PSU is subsampled was implemented in the FRA 1990 design, but was not present in any other design included in this review. Systematic sampling is used at some stage of the sampling design in the FRA 1990, FRA 2010, TREES II, and the Canadian inventory (Leckie et al. 2002). Simple random selection, usually within strata, was used in the applications of Hansen et al. (2008, 2010), Dymond et al. (2008), and the surveys of Great Britain (Levy and Milne 2004).

5.4 Studies Evaluating Sampling Design Options

As the first noteworthy effort to employ sampling of remotely sensed data to monitor forests, the FRA 1990 remote sensing survey triggered a series of studies evaluating the effectiveness of sampling for forest monitoring using remotely sensed data. An early and influential study by Tucker and Townshend (2000) expressed concern that the FRA 1990 sampling approach would not yield sufficiently precise estimates of deforestation unless the sample size was extremely large. Tucker and Townshend's (2000) conclusions were based on an investigation of deforestation for country-specific estimation for Bolivia, Colombia, and Peru. The populations evaluated were based on complete coverage deforestation for these countries. Each country was partitioned by Landsat scenes (41, 61, and 45 for Bolivia, Colombia, and Peru, respectively), and the variability of sample-based estimates for simple random sampling of these scenes was evaluated. Tucker and Townshend (2000) found that a large proportion of the available scenes had to be sampled to obtain precise estimates of deforestation. Sanchez-Azofeifa et al. (1997) also noticed that high variances of deforestation estimates could occur when the sampling unit was a satellite scene. Sanchez-Azofeifa et al. (1997) examined a population of 202 Landsat scenes from the Brazilian Amazon for which complete coverage change information was available. They demonstrated that a stratified design with strata defined by "persistence" improved the precision of the sample estimates relative to simple random sampling, where Sanchez-Azofeifa et al. (1997, 183) defined persistence in terms of "scenes presenting some degree of deforestation on time Ti will present more but no less deforestation between time Ti and time Ti+1 of total deforestation." Czaplewski (2003) presented evidence to indicate that the problems encountered by these studies were diminished when sampling was applied to larger regions, such as continental or global estimates of deforestation.

These early studies initiated a healthy debate of central issues of the sampling approach including the choice of sampling unit and the trade-offs between cost and variability of sampling more but smaller sampling units. These initial studies focused on Landsat scenes as the sampling unit, but relatively quickly (e.g., Tomppo et al. 2002; Stehman et al. 2003) it became apparent that using such a large sampling unit was a major contributor to the poor performance of the sampling approach observed by Tucker and Townshend (2000) and Sanchez-Azofeifa et al. (1997). Tucker and Townshend's (2000) Bolivia population of $N = 41$ Landsat-based sampling units included one unit that comprised 40% of the total deforestation of the region, and four scenes accounted for 70% of the total deforestation of Bolivia. Tucker and Townshend's (2000) analysis of the Bolivia population is noteworthy because it identified that one or a few units with very high deforestation may occur and have substantial impact on the standard error of the sample-based estimate of change. Outliers and their effect on the precision of estimated change is an issue to be taken seriously. The shift to using sampling units smaller than Landsat scenes diminishes the impact of such outliers on the precision of the area estimates.

Tomppo et al. (2002) continued the evaluation of potential designs for continental and global forest assessments such as the FRA. Their results were based on a meticulously constructed hypothetical population of deforestation. Two sizes of sampling units were evaluated: a 150 km × 150 km sampling unit (corresponding approximately to the area of a Landsat image) and a 10 km × 10 km sampling unit. Stratification was implemented geographically using 10 FRA ecological zones to control the distribution of the sample among zones, and an additional level of stratification was defined using the Dalenius–Hodges rule (Cochran 1977) to determine strata boundaries based on the continuous variable Advanced Very High Resolution Radiometer (AVHRR) change. The sample was then allocated equally to five strata created within each geographic stratum. Tomppo et al. (2002) found that the 10 km × 10 km unit was more effective than the 150 km × 150 km unit when the stratified sampling design was implemented. Further, stratification by AVHRR change improved the standard errors of the estimates.

The planned use of systematic sampling for the FRA 2010 remote sensing survey prompted several studies investigating this design. As noted earlier, the FRA 2010 sampling design is a systematic sample of 10 km × 10 km blocks located at the intersections of the 1° lines of latitude and longitude. Steininger et al. (2009) evaluated the estimates that would be obtained from the FRA 2010 design if that design were to be applied to digital maps of deforestation for six regions (the five countries of Bolivia, Colombia, Ecuador, Peru, and Venezuela and the Brazilian Amazon) and the area represented by all six regions combined. This study also included a comparison of different size sampling units ranging from 5 km × 5 km to 50 km × 50 km and investigation of various grid densities (0.25° intersections of latitude and longitude up to 2° intersections). Steininger et al. (2009) concluded that the FRA design is clearly acceptable at the continental level, but country-specific estimates may be problematic. For a fixed sample size, a larger sample unit is obviously better, but Steininger et al. (2009) present results that provide insight into the trade-offs between smaller standard errors but increasing cost as the area of the sampling units increases.

Eva et al. (2010) conducted a study analogous to that of Steininger et al. (2009) to evaluate the performance of the FRA 2010 design estimates when applied to French Guiana (1990–2006 change) and the Brazilian Legal Amazon (BLA) (2002–2003 change). Again complete coverage deforestation information derived from Landsat imagery was the basis for evaluating the sample-based estimates. The sampling unit was 20 km × 20 km, and the sample size was $n = 330$ for the BLA. The estimated standard error of 0.10 million ha (based on nine replicate samples of the 1° intersections of latitude and longitude) obtained for the BLA is miniscule relative to the estimate of 2.81 million ha of deforested area. For French Guiana, the systematic sample was intensified to 0.25° grid intersections (a 16-fold increase over the standard FRA grid spacing of 1° intersections), resulting in a sample size of 108 sample units (approximately 12% of the total area), and the size of the sampling unit was reduced to 10 km × 10 km. For this intensified sample, the estimated standard error was about 6.8% of the estimated area of deforestation. The design of the Eva et al. (2010) study did not include comparison of systematic sampling to simple random sampling, but it can be expected that the systematic design improved upon the standard errors that would have been obtained from simple random sampling.

Broich et al. (2009) investigated the relative precision of systematic, stratified random, and simple random sampling using a population of Landsat-derived 2000–2005 deforestation for the BLA. The strata were based on MODIS-derived change for the 18.5 km × 18.5 km units partitioning the study region. The systematic sampling design was modeled after the FRA 2010 design of sampling at 1° intersections of latitude and longitude and an intensified version of that design with sampling units at 0.5° intersections. Broich et al. (2009, table 3 and table 4) found that both systematic and stratified sampling were improvements over simple random sampling, and both were operationally very effective for estimating deforestation based on the standard errors relative to the annual rate of deforestation for the study area (population) that was 0.55% (percent of area). The 1° systematic sample (325 sample units) yielded a standard error of 0.05%, the stratified random sample (150 sample units) yielded a standard error of 0.03%, and the 0.5° systematic sample (1,310 sample units) yielded a standard error of 0.02%. For this particular study, the stratified design was more effective than systematic sampling, the advantage being attributable to the effectiveness of the MODIS-based stratification. Further investigation would be needed to confirm the utility of a similar approach to stratification for other locations and different time periods.

Stehman et al. (2011) used the same population of deforestation for the BLA investigated by Broich et al. (2009) to demonstrate the utility of stratified random sampling for adapting a global forest monitoring design to achieve regional reporting objectives. The stratified sampling design employed by Hansen et al. (2008) for the humid tropical forests could be augmented using the same stratified design to address the objective of estimating deforestation by states within the BLA. The ability to augment a stratified continental or global sample parallels the use of an intensified systematic sample (Eva et al. 2010) to produce country- or region-specific estimates for the FRA 2010 design. The analyses also permitted comparing the standard errors for simple random, systematic, and stratified random sampling for the states within the BLA. When compared on the basis of equal sample size, both systematic and stratified random sampling were better than simple random sampling, and for most states, stratified random sampling had a smaller standard error than systematic sampling (Stehman et al. 2011, table 5). Similar to the precautions expressed for interpreting the Broich et al.'s (2009) results, the strong advantage gained by the MODIS-based stratification in the BLA would not necessarily extend to other geographic locations or time periods.

These evaluative studies have progressed from the precautionary findings revealed by Tucker and Townshend (2000) to strong confirmation that the sampling approach can yield estimates with relatively small standard errors. However, the sampling design must be chosen based on recognizing some of the potential pitfalls, the foremost of which is that very large sampling units (e.g., Landsat scenes) should be avoided. The evaluative studies support the results of the actual applications (Section 5.3) of sample-based estimates of forest change in that the small standard errors observed in practice are substantiated by empirical investigation of the sampling designs applied to known populations of deforestation.

The majority of the research examining different sampling design options has focused on the basic sampling designs outlined in Section 5.2.1 (systematic, stratified random, and cluster sampling). Several designs outside this traditional realm have been considered. Magnussen et al. (2005) evaluated adaptive cluster sampling (ACS), a sampling design that is advocated as efficient and practical for rare but spatially clustered phenomena, exactly a scenario often envisioned for forest cover change. Magnussen et al.'s (2005) general recommendation was that "ACS remains attractive when the average cost of adaptively adding a PU [population unit] to the initial sample is low relative to the average cost of sampling a PU at random." This condition would not be met when working with a satellite scene as the PU. If the PU is smaller than a Landsat scene, for example, when using a 10 km × 10 km unit, the condition described may be satisfied because if the adaptive procedure calls for additional PUs (the 10 km × 10 km units) within a scene in which other PUs have been interpreted, this would be less costly than obtaining a new PU in a different Landsat scene. Magnussen et al. (2005) expressed several additional reservations regarding the use of ACS, noting that practical experience with ACS is still limited and that design effects (i.e., precision improvements) and costs can be highly variable. They further noted that it is likely that a rule for terminating the adaptive selection process would be needed to avoid cost overruns (i.e., to avoid uncontrolled progression to selecting new sample units from the adaptive steps of the protocol), thus adding complexity to the design, and that the effect of population structure on ACS is so complex that it is difficult to predict success of ACS for a given application. ACS is more complex to implement and analyze, so the advantages gained must be sufficient to overcome this burden of greater complexity.

When stratified sampling is used to increase the sample size of sampling units with anticipated high forest cover change, the design is an example of an unequal probability sampling design. That is, the inclusion probabilities for units in different strata are different. The extension of unequal probability sampling to a design for which the inclusion probabilities are proportional to an auxiliary variable x (denoted as πpx designs) is another option to consider.

Giree (2011) implemented a πpx design in a study of gross forest cover loss in Malaysia, where x was the area of change derived from AVHRR for 1990–2000. The rationale for implementing a πpx design instead of a stratified design was related to the options for estimation (Section 5.2.4). A special case of the general regression estimator applicable to a stratified random design is the separate regression estimator, and this estimator requires a sample size of 25–30 per stratum to ensure that the estimator is not biased. Because the sample size for the entire Malaysia study was a modest n = 25 units (each 18.5 km × 18.5 km), a stratified design combined with the separate regression estimator would have been a risky proposition. The πpx design allowed the option to use the auxiliary variable x to increase the sample size of higher change units, and the general regression estimator could still be applied to the sample of 25 units without concern for bias attributable to a small sample size. For the πpx design implemented and using the Horvitz–Thompson estimator (Equation 5.1), Giree (2011) estimated the annual gross forest cover loss for Malaysia during 1990–2000 to be 0.43 million ha per year with a standard error of 0.04 million ha per year. Thus despite the small sample size, the πpx design yielded a reasonably small standard error relative to the estimated rate of deforestation.

The sample obtained by Giree (2011) is useful to illustrate the application of model-based inference. Suppose that Y_i is the area of deforestation for 1990–2000 obtained from Landsat and x_i is the area of deforestation obtained from AVHRR on unit i (where each unit is 18.5 km × 18.5 km). The AVHRR value (x_i) is available for all N = 958 units comprising Malaysia (i.e., the entire population), but the Landsat deforestation is available for only the n = 25 sample blocks selected by the πpx design described in the preceding paragraph. Following Valliant et al. (2000, section 5.5.1), suppose that the model relating Y_i to x_i is a quadratic model of the form

$$Y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + e_i,$$

where e_i is distributed with mean 0 and variance $v_i = x_i^2\sigma^2$. The predicted value for unit (block) i, $i = 1,\dots,N$, is

$$\hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_i + \hat{\beta}_2 x_i^2$$

where the estimates of the β's are obtained by least squares. If s denotes the elements selected for the sample and r denotes the remaining (not sampled) elements in the population, the model-based estimator for the population total (based on the model specified above) is

$$T = \sum_s Y_i + \sum_r \hat{Y}_i$$

The estimator T does not take into consideration that the sampling design was πpx and instead is entirely dependent on the specified model. The "prediction theory" basis of the estimator is also apparent because the second term of T is a sum of the predicted values of Y_i for the elements of the population that were not observed in the sample. For the Giree (2011) sample data for 1990–2000 deforestation in Malaysia, the model-based estimator is 0.35 million ha per year (slightly below the 0.43 million ha per year for the design-based estimate). The standard error for the model-based estimate was 0.07 million ha per year (based on the specified model and equation 5.1.6, p. 130 of Valliant et al. 2000). Although it is tempting to compare the standard errors of the design-based and model-based estimators, the two approaches to inference employ very different definitions of variability, and it does not seem relevant to compare variances that constitute very different representations of uncertainty. In practice, the analysis using a model-based estimator should include evaluation of competing models and an assessment of the goodness of fit of the data to model assumptions. These details are omitted for reasons of brevity.

5.5 Discussion of Sampling Applications and Evaluative Studies

Several general tendencies emerge from this review of applications and evaluative studies of forest monitoring sampling designs for remotely sensed data. The degree to which the sampling design is tailored to the spatial characteristics of the satellite imagery ranges from a strong dependence in which Landsat scenes or quarter scenes are used as the sampling units (Richards et al. 2000; Tucker and Townshend 2000; Czaplewski 2003; Gallego 2005) to virtually no dependence on the imagery for defining sampling units (Leckie et al. 2002; Levy and Milne 2004; Mayaux et al. 2005; Hansen et al. 2008, 2010). Gallego (2005) notes that choosing the size of the sampling unit to correspond to the specific imagery to be used to interpret forest cover or change is justified when working with sensors with approximately fixed image frames (e.g., Landsat TM), but otherwise becomes more complicated. In a long-term monitoring program, or in cases where several sources of imagery might be used, the advantages of choosing the sampling unit linked to a single imaging framework are diminished.

For studies covering continental or global change, an initial stratification by biomes, ecoregions, or other large areas is typically implemented, although the FRA remote sensing survey is a notable exception. Geographic strata are typically meaningful regions for reporting results, and they also serve to aggregate relatively homogeneous forest types together, which may be advantageous for better precision of continental or global estimates of change. In most of these studies targeting the objective of estimating the area of forest change, stratification based on a proxy or surrogate for true change must be used. The goal is to create strata in which change is relatively uniform within each stratum, thus creating smaller within-stratum variances. Stratification also allows for increasing the sample size in the higher variability strata.

Many of the desirable design criteria specified in Section 5.2.5 are prominent in the sampling designs implemented in practice for forest monitoring using remotely sensed data. All of the sampling designs reviewed in this chapter satisfy the conditions defining a probability sampling design. This noteworthy feature suggests that the importance of rigorous design-based inference combined with a probability sampling design has been recognized at the design planning stage. Most of the applications reviewed met the second desirable design criterion of being simple to implement. The two most commonly used sampling designs, systematic (e.g., the FRA 2010 design) and stratified random (e.g., Dymond et al. 2008; Hansen et al. 2008, 2010), are straightforward to implement. The two examples of more complex sampling designs presented in this chapter were ACS, investigated by Magnussen et al. (2005), and sampling with probability proportional to an auxiliary variable x, where x could be a measure of forest cover loss from coarser resolution imagery (Giree 2011) or x could simply be the area (size) of each element in the partition of the universe (Gallego 2005). A majority of the designs reviewed included some capacity for distributing the sample spatially (criterion 4), either by implementing a systematic selection protocol or by incorporating geographic stratification. The sampling designs implemented in practice (Section 5.3) produced standard errors that were small enough that the estimates would likely be viewed as credible for most uses of the estimates (criterion 5).

An unbiased estimator of variance is not available for systematic sampling, and the estimated variance is then based on an approximation (desirable design criterion 6). A simple approximation is to use a variance estimator appropriate for simple random sampling, and this approximation is typically a biased overestimate of the variance for the systematic design. Such an overestimate of variance is often acceptable because it is conservative (i.e., it does not under-report the uncertainty of the estimate), but a conservative estimate also will not reflect the true precision of the estimate. Thus it may be that systematic sampling has produced a very precise estimate, but the estimated standard error, being a conservative overestimate, will not reflect that precision. Stratified random sampling does permit an unbiased estimator of variance.

Most sampling designs can be implemented in a manner that will allow for changing the sample size "in progress" (criterion 7). Simple random and stratified random protocols are particularly easy to truncate to reduce the target sample size or extend to increase the target sample size while still maintaining the fundamental features of the design (Stehman et al. 2011). Intensifying a systematic sample is straightforward simply by changing the grid density (e.g., decreasing the distance between grid points by half increases the sample size fourfold). Less severe changes in sample size will require breaking up the strict grid structure. For example, to add 10 new sample units, the original grid spacing could be halved and 10 units selected at random from the introduced new grid points. To reduce the sample size from the initial grid, sample units could be randomly deleted, although this assumes that the existing sample up to the point of sample termination had been selected in a random order. Both of these sample size modifications of a systematic grid will produce a final sample that does not adhere exactly to the initial full grid structure and will therefore diminish some of the advantages of the systematic sample.

The last desirable design criterion, "transparency," is difficult to assess because it depends on individual experience with sampling methods and theory. The designs implemented in practice for forest monitoring (Section 5.3) are probability sampling designs, which conveys a strong element of transparency to the process if one is familiar with the theory of design-based inference and estimation. Systematic sampling is intuitively appealing and therefore transparent to nonscientists because of the uniform spatial distribution of the sample across a region and because of the obvious explanation for why sample points are located where they are. A probability sample based on simple random selection may be misconstrued by laypersons as having been subjectively selected to focus on specific locations to bias the results in a particular fashion. Similarly, intensifying the sampling effort within some strata may be misunderstood by laypersons as an effort to increase the sample size within areas of high deforestation, thus "obviously" biasing the estimates in the minds of those not aware of the weighted estimation approaches required with unequal probability sampling designs (see Equations 5.1 and 5.2). It is an interesting question of how individual perceptions (e.g., various levels of understanding of sampling theory and practice) should influence the decision-making process when considering different sampling design options for a given application.

5.6 Sampling for Forest Monitoring Using Remotely Sensed Data: A Look Ahead

Despite past operational successes of remote sensing–based forest monitoring using a sampling approach, much room for improvement exists to develop more accurate, more precise, and more cost-effective methods. One of the biggest concerns with forest monitoring by remote sensing is measurement error—are the remote sensing measurements of forest attributes such as cover or deforestation sufficiently accurate? Measurement error can be viewed as having two components: bias and variability. Measurement bias refers to a consistent over- or under-representation of the true value of the response, and measurement variability refers to the differences in the observed response over multiple replications of the measurement process (Särndal et al. 1992). For example, if the area of deforestation for a 10 km × 10 km unit is obtained by a human interpreter working with satellite imagery or aerial photographs, we can envision replicated realizations of this measurement by different interpreters. If the average result of these repeated observations of deforestation differs from the true value of the unit, measurement bias is present. If the repeated observations vary from interpreter to interpreter, measurement variability is present. It is straightforward to quantify measurement variability by having different interpreters examine the same sampling unit, but it is less obvious how to quantify measurement bias.

A fundamental premise of the sampling approach to forest monitoring is that the best available protocols for obtaining the target forest measurements are being used. The assessment of measurement bias would require that a more accurate measurement protocol existed, and that it would be possible to estimate measurement bias based on what would likely be a relatively small sample (i.e., if a larger sample size using the more accurate protocol were available, this measurement protocol would be the basis of the monitoring estimates). For example, if Landsat is the best-quality imagery that can be affordably used in a sample-based monitoring program, then it would be possible to spot check the Landsat interpretations using very high-resolution imagery and a more detailed (i.e., more accurate) interpretation protocol, and this would provide a way to assess measurement bias. Specific sampling designs to incorporate the assessment of measurement error have not received much attention.

Another challenging question is how to construct the sampling design for long-term forest monitoring based on remotely sensed data. A number of factors play into this decision. Over time, it is possible that improved methods (e.g., better imagery, more accurate classification methods) will be developed for measuring the forest characteristics of interest. The sampling design should be able to incorporate these improved options. For example, if new sources of imagery prove to be better, the sampling design must be able to accommodate a potential change in the footprint of different imagery. A good illustration of this problem is the early emphasis on using Landsat scenes as sampling units. Even if these large sample units had proven to be effective for use with Landsat, it is likely that smaller sampling units would now be more desirable for the very high-resolution imaging options that subsequently have become available.

A number of challenging questions remain to be resolved regarding the three primary decisions that determine a sampling design (Section 5.2.1). Consider the cluster sampling decision first. The primary advantage of cluster sampling is the savings in time and cost of working with a sample that is spatially constrained in the sense that the sample may be controlled to fall within a fixed number of clusters or PSUs. When working with a specific source of imagery, cluster sampling allows for controlling the number of images that must be processed (e.g., a Landsat or an IKONOS image). Gallego (2012) demonstrated that sampling a relatively small number of SSUs within each PSU is adequate from the standpoint of statistical precision, and little advantage is gained by one-stage cluster sampling. The qualitative nature of Gallego's (2012) result is not surprising, but the quantitative revelation that such a small number of SSUs would generally be adequate is eye opening. Gallego's (2012) result suggests that two-stage cluster sampling should be given serious consideration. One-stage cluster sampling may still be a good design option for other reasons (e.g., when landscape pattern and other landscape context information is desirable), but two-stage sampling is clearly a strong option when estimating area is the primary objective.

Although stratification has been demonstrated to be effective for estimating area (Tomppo et al. 2002; Broich et al. 2009; Stehman et al. 2011), the precautions noted about the portability of these results to other regions for which forest change dynamics may be different should be heeded. In a long-term forest monitoring setting, the benefit of stratification would almost surely diminish over time. However, it may still be worthwhile to include stratification simply because estimating a relatively rare event such as change with acceptably small standard errors may be difficult otherwise. If the monitoring is retrospective (e.g., estimating forest change from 1980 to 2010), then even though multiple time periods of change may be of interest (e.g., every 5-year period), it may still be possible to develop an effective stratification based on change throughout the full monitoring period. Because archival imagery and other information exist pertaining to changes that have taken place, it is possible to stratify by change based on auxiliary information. In the design of a forward-looking (prospective) monitoring program, the ability to choose an effective stratification may become more tenuous. In the prospective setting, the strata must be defined by expected change if the sample data must be obtained in real time (i.e., when it is not feasible to use archival imagery).

For long-term monitoring with periodic reporting (e.g., 5-year time periods), the question of permanent sample plots versus allowing the sample locations to change over time is another important consideration. For example, if estimates are desired for each 5-year period over a 30-year total period of monitoring, sample locations will need to be paired (i.e., the initial and end date) for any given 5-year period to estimate gross change. But the decision of whether to use permanent plots for the entire 30-year monitoring window will depend on the situation. For example, in a region of rapid cycling from forest clearing to regrowth to clearing, the 30-year time series from permanent plots may prove invaluable. Conversely, in a less dynamic region in which at most one change will occur in the 30-year period, it may be advantageous to focus more on the individual 5-year estimates. This may lead to implementing a stratification that is advantageous for each 5-year estimate, but not necessarily a stratification useful for any other time period, and consequently a new set of paired plots would be selected for each 5-year period. In a prospective monitoring program, particularly one that may have regulatory ramifications, it would be preferable to have the sample locations "hidden" from the parties involved so that forest management of the sample locations is not different from forest management of the general population. However, not revealing sample locations would seem to conflict with the desirable design criterion of transparency. Consequently, permanent plot locations for prospective regulatory monitoring could be problematic. If new sample locations are selected for each reporting interval, these problems with permanent plots would be avoided. Sampling design decisions will be strongly influenced by practical considerations. Additionally, studies investigating the precision of permanent sample locations versus more flexible sample arrangements should be conducted for various scenarios of forest change.

Two-phase sampling is often an effective design for general-purpose monitoring (see Fattorini et al. 2004 for a specific example application) and has a relatively long history of use for forest inventory. In two-phase sampling, a large first-phase sample is selected, and one or more auxiliary variables are measured for each unit sampled. A second-phase sample is then selected, typically from the first-phase sample units, and the target measurements are obtained for the smaller second-phase sample. In contrast to two-stage cluster sampling in which the sampling units are different sizes for the two stages, it will be assumed that the sampling units are defined similarly at both phases for two-phase sampling. The auxiliary information from the larger first-phase sample may be used in two ways. One option is to use the auxiliary variables in a model-assisted estimator. The other option is to use the auxiliary information to stratify the first-phase sample units and to then select a stratified sample at the second phase. Two-phase sampling for stratification is a practical option when it is not feasible to stratify all N elements of the universe.

5.7 Conclusions

The complete coverage mapping and sampling-based approaches should coexist in a forest monitoring program as both approaches address important and sometimes different objectives. The full coverage, spatially explicit information provided by maps is an invaluable resource. But typically there will be higher quality information than what was used to construct the map, and this higher quality information becomes affordable and practically manageable for only a sample of the full region. Thus a sample in which higher quality imagery and more accurate measurement protocols can be applied becomes the basis of an estimate for aggregate properties of the forest characteristics to be monitored. The sample-based approach to monitoring forest cover and change in forest cover has been proven to be operationally effective in a number of studies. Efforts to refine these methods to produce more accurate and precise estimates of forest characteristics should continue to take advantage of new developments of higher quality imagery and better classification methods.

About the Contributor

Stephen V. Stehman has been employed at State University of New York–College of Environmental Science and Forestry, New York (SUNY ESF), since 1989. He teaches courses in sampling methods and design of experiments and provides statistical consulting service for faculty and students. Stehman was introduced to sampling designs for environmental monitoring while working for Scott Overton during the design phase of the United States Environmental Protection Agency's Environmental Monitoring and Assessment Program (EMAP). Stehman also conducts research on sampling design and analysis methods for assessing accuracy of land cover and land cover change maps.

References

Achard, F. et al., Determination of deforestation rates of the world's humid tropical forests. *Science*, 297, 999, 2002.

Broich, M. et al., A comparison of sampling designs for estimating deforestation from Landsat imagery: A case study of the Brazilian Legal Amazon. *Remote Sensing of Environment*, 113, 2448, 2009.

Cochran, W.G., *Sampling Techniques* (3rd edn.). Wiley, New York, 1977.

Corona, P., Integration of forest mapping and inventory to support forest management. *iForest*, 3, 59, 2010.

Czaplewski, R.L., Can a sample of Landsat sensor scenes reliably estimate the global extent of tropical deforestation? *International Journal of Remote Sensing*, 24, 1409, 2003.

Duveiller, G. et al., Deforestation in Central Africa: Estimates at regional, national and landscape levels by advanced processing of systematically-distributed Landsat extracts. *Remote Sensing of Environment*, 112, 1969, 2008.

Dymond, J.R. et al., Estimating area of forest change by random sampling of change strata mapped using satellite imagery. *Forest Science*, 54, 475, 2008.

Eva, H. et al., Monitoring forest areas from continental to territorial levels using a sample of medium spatial resolution satellite imagery. *ISPRS Journal of Photogrammetry and Remote Sensing*, 65, 191, 2010.

FAO, *Forest Resources Assessment 1990: Survey of Tropical Forest Cover and Study of Change Processes*. FAO Forestry Paper 130, FAO, Rome, 1996.

FAO, *The 2010 Global Forest Resources Assessment Remote Sensing Survey: An Outline of Objectives, Data, Methods, and Approach*. FAO Forest Resources Assessment Working Paper 155, FAO, Rome, 2009.

Fattorini, L., Marcheselli, M., and Pisani, C., Two-phase estimation of coverages with second-phase corrections. *Environmetrics*, 15, 357, 2004.

Fuller, R.M., Wyatt, B.K., and Barr, C.J., Countryside survey from ground and space: Different perspectives, complementary results. *Journal of Environmental Management*, 54, 101, 1998.

Gallego, F.J., Remote sensing and land cover area estimation. *International Journal of Remote Sensing*, 25, 3019, 2004.

Gallego, F.J., Stratified sampling of satellite images with a systematic grid of points. *ISPRS Journal of Photogrammetry & Remote Sensing*, 59, 369, 2005.

Gallego, F.J., The efficiency of sampling very high resolution images for area estimation in the European Union. *International Journal of Remote Sensing*, 33, 1868, 2012.

Giree, N., Quantifying gross forest cover loss in Malaysia between 1990 and 2005, Unpublished MS Thesis, South Dakota State University, Brookings, SD, 2011.

Hansen, M.C., Stehman, S.V., and Potapov, P.V., Quantification of global gross forest cover loss. *Proceedings of the National Academy of Sciences*, 107, 8650, 2010.

Hansen, M.C. et al., Humid tropical forest clearing from 2000 to 2005 quantified using multi-temporal and multi-resolution remotely sensed data. *Proceedings of the National Academy of Sciences*, 105, 9439, 2008.

Hassett, E.M., Stehman, S.V., and Wickham, J.D., Estimating landscape pattern metrics from a sample of land cover. *Landscape Ecology*, 27, 133, 2012.

Leckie, D.G., Gillis, M.D., and Wulder, M.A., Deforestation estimation for Canada under the Kyoto Protocol: A design study. *Canadian Journal of Remote Sensing*, 28, 672, 2002.

Levy, P.E. and Milne, R., Estimation of deforestation rates in Great Britain. *Forestry*, 77, 9, 2004.

Magnussen, S. et al., Adaptive cluster sampling for estimation of deforestation rates. *European Journal of Forest Research*, 124, 207, 2005.

Mayaux, P., Achard, F., and Malingreau, J.-P., Global tropical forest area measurements derived from coarse resolution satellite imagery: A comparison with other approaches. *Environmental Conservation*, 25, 37, 1998.

Mayaux, P. et al., Tropical forest cover change in the 1990s and options for future monitoring. *Philosophical Transactions of the Royal Society B*, 360, 373, 2005.

Overton, W.S. and Stehman, S.V., The Horvitz-Thompson theorem as a unifying perspective for probability sampling: With examples from natural resource sampling. *American Statistician*, 49, 261, 1995.

Potapov, P. et al., Combining MODIS and Landsat imagery to estimate and map boreal forest cover loss. *Remote Sensing of Environment*, 112, 3708, 2008.

Richards, T., Gallego, J., and Achard, F. Sampling for forest cover change assessment at the pan-tropical scale. *International Journal of Remote Sensing*, 21, 1473, 2000.

Ridder, R.M., *Global Forest Resources Assessment 2010. Options and Recommendations for a Global Remote Sensing Survey of Forests*. FAO Forest Resources Assessment Working Paper 141, FAO, Rome, 2007.

Sanchez-Azofeifa, G.A., Skole, D.L., and Chomentowski, W., Sampling global deforestation databases: The role of persistence. *Mitigation and Adaptation Strategies for Global Change*, 2, 177, 1997.

Särndal, C.-E., Swensson, B., and Wretman, J., *Model-Assisted Survey Sampling*. Springer-Verlag, New York, 1992.

Stehman, S.V., Comparing estimators of gross change derived from complete coverage mapping versus statistical sampling of remotely sensed data. *Remote Sensing of Environment*, 96, 466, 2005.

Stehman, S.V., Sohl, T.L., and Loveland, T.R., Statistical sampling to characterize land-cover change in the U.S. Geological Survey land-cover trends project. *Remote Sensing of Environment*, 86, 517, 2003.

Stehman, S.V. et al., Adapting a global stratified random sample for regional estimation of forest cover change derived from satellite imagery. *Remote Sensing of Environment*, 115, 650, 2011.

Steininger, M.K., Godoy, F., and Harper, G., Effects of systematic sampling on satellite estimates of deforestation rates. *Environmental Research Letters*, 4, 034015, 2009.

Tomppo, E., Czaplewski, R., and Mäkisara, K., *The Role of Remote Sensing in Global Forest Assessments*. FAO Forest Resources Assessment Working Paper 61, FAO, Rome, 2002.

Tucker, C.J. and Townshend, J.R.G., Strategies for monitoring tropical deforestation using satellite data. *International Journal of Remote Sensing*, 21, 1461, 2000.

Valliant, R., Dorfman, A.H., and Royall, R.M., *Finite Population Sampling and Inference: A Prediction Approach*. Wiley, New York, 2000.