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Land Cover Change Detection

John Rogan
Clark University

Nathan Mietkiewicz
Clark University

Acronyms and Definitions

ALI	Advanced Land Imager
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
AutoMCU	Automated Monte Carlo Unmixing
AVHRR	Advanced Very High Resolution Radiometer
AVHRR NDVI3g	Third-generation GIMMS NDVI from AVHRR sensors
B	Brightness band derived from the Tasseled Cap transformation
BG	Bare ground
B_r	Rescaled brightness band
CLASlite	Carnegie Landsat Analysis System–Lite
CONUS	Contiguous United States
DI	Disturbance index
DI′	Disturbance index prime
dNBR	Delta Normalized Burn Ratio
EROS	Earth Resources Observation and Science
EVI	Enhanced vegetation index
FIA	Forest Inventory Analysis
G	Greenness band derived from the Tasseled Cap transformation
GIMMS	Global Inventory Modeling and Mapping Studies
GIS	Geographic information systems
GPS	Global Positioning System
G_r	Rescaled greenness band
LAI	Leaf area index
Landsat ETM+	Landsat Enhanced Thematic Mapper+
Landsat OLI-TIRS	Landsat Operational Land Imager–Thermal Infrared Sensor
Landsat TM	Landsat Thematic Mapper
LandTrendr	Landsat-based Detection of Trends in Disturbance and Recovery
LCMMP	California Land Cover Mapping and Monitoring Program
LST	Land surface temperature
MaFoMP	Massachusetts Forest Monitoring Program
MGDI	MODIS Global Disturbance Index
MODIS	Moderate-Resolution Imaging Spectro radiometer
MTBS	Monitoring Trends in Burn Severity
NDVI	Normalized difference vegetation index
NDWI	Normalized difference wetness index
NPV	Nonphotosynthetic vegetation
NRCS	Natural Resources Conservation Service
PAR	Photosynthetically active radiation
SPOT	Satellite Pour l'Observation de la Terre
STAARCH	Spatial Temporal Adaptive Algorithm for mapping Reflectance Change
STARFM	Spatial and Temporal Adaptive Reflectance Fusion Model

UN-REDD	United Nations Programme on Reducing Emissions from Deforestation and Forest Degradation
USDS-FS	United States Department of Agriculture Forest Service
USGS	United States Geological Survey
USGS-LCCP	United States Geological Survey Land Cover Characterization Program
VCT	Vegetation change tracker
W	Wetness band derived from the Tasseled Cap transformation
WELD	Web-Enabled Landsat Data
W_r	Rescaled wetness band

21.1 Introduction

The purpose of this chapter is to explore the current trends in land cover change detection and to identify those trends that are potentially transformative to our understanding of land change, as well as identify knowledge/information gaps that should require attention in the future. The current level of understanding of the scale and pace of land cover change is inadequate (Frey and Smith 2007; Turner et al. 2007; Hansen et al. 2013). However, it is understood that land cover change is an undisputed component of global environmental change (Kennedy et al. 2014). Land cover changes and their impacts range widely from regional temperature warming to land degradation and biodiversity loss and from diminished food production to the spread of infectious diseases (Vitousek et al. 1997; Farrow and Winograd 2001). Land cover change, manifested as either land cover modification or conversion, can occur at all spatial scales, and changes at local scales can have cumulative impacts at broader scales (Stow 1995).

The long-standing challenge facing scientists and policy makers are the paucity of comprehensive data, at local, regional, and national levels, on the types and rates of land cover changes, and even less systematic evidence on the causes/drivers and consequences of those changes (Walker 1998). Such data can be generated through a dual approach: (1) based on direct or indirect observations, for the regions and time periods for which data exist (Franklin 2002), and (2) based on projections by models (Lambin et al. 1999). A key element for the successful implementation of this dual approach is the monitoring of land cover on a systematic, operational basis (Strahler et al. 1996; Lunetta and Elvidge 1998; Townshend and Justice 2002; Wulder and Coops 2014).

In data-rich locations, such as the United States, federal resource inventory programs, such as the U.S. Forest Service Forest Inventory and Analysis (FIA) program (Gillespie et al. 1999) and the Natural Resources Conservation Service (NCRS 2000), have provided valuable statistical information on land cover dynamics for over 35 years. These agencies provide plot-level information for remote sensing land cover mapping projects (Franklin et al. 2000). However, there is also a need for spatially explicit, thematically comprehensive data products that can be provided by remotely sensed data (Loveland et al. 2002). For example, the U.S. Geological Survey's Land Cover Characterization Program (USGS-LCCP) is designed to document the rates, causes, and consequences of land cover change from 1973 to present, using Landsat North American Landscape Characterization (NALC) data (Soulard et al. 2014). The program area spans 84 ecoregions of the conterminous United States. Another example of comprehensive large-area land cover assessment is the Canadian Forest Service Earth Observation for Sustainable Development of Forests (EOSD) program (http://www.nrcan.gc.ca/), which monitors Canada's forest cover with Landsat imagery (Wood et al. 2002). Additionally, the European Coordination of Information on the Environment (CORINE) program (http://land.copernicus.eu/pan-european/corine-land-cover) maps land cover and land use (LCLU) (44 categories) using a variety of medium-resolution satellite data from 1990 to present.

In data-poor locations, data derived from remote sensing are often the only source of information available for land cover monitoring (Lambin et al. 1999). This situation places added pressure on remote sensing practitioners to produce accurate change maps using replicable methods, which cannot be verified using the traditional suite of map accuracy tools (Rogan and Chen 2004; Dorais and Cardille 2011). The inclusion of land cover change in international agreements such as the Kyoto Protocol under the United Nations Framework Convention on Climate Change (UNFCC), as well as the growing popularity of the United Nations Programme on Reducing Emissions from Deforestation and Forest Degradation (UN-REDD and REDD+), makes it essential to advance initiatives to monitor land cover change effectively (DeFries and Townsend 1999). Increased Landsat data availability (Wulder and Coops 2014) and the growing trend in automated mapping and change detection algorithms will likely open up the current data bottleneck such that developing countries can create more precise estimates of land change (Zhu and Woodcock 2014).

In addition to the technical advantages of remotely sensed data, the reduced data cost, increased accessibility and availability, and increased understanding of the information derived from these data have facilitated the launch of large-area remote sensing–based monitoring programs/initiatives (Loveland et al. 2002; Eidenshink et al. 2007), as well as global-scale medium spatial resolution change map data sets (Hansen et al. 2013). Therefore, these data, in concert with enabling technologies such as global positioning systems (GPSs) and geographic information systems (GISs), can form the information base upon which sound and cost-effective monitoring decisions can be made (Lunetta 1998).

While a large body of work has accumulated regarding land cover change monitoring using remotely sensed data (e.g., see reviews by Nelson 1983; Singh 1989; Hobbs 1990; Mouat et al. 1993; Stow 1995; Coppin and Bauer 1996; Macleod and Congalton 1998; Ridd and Liu 1998; Mas 1999; Civco et al. 2002; Coppin et al. 2002, 2004; Gong and Xu 2003; Wulder and Franklin 2006), little guidance exists for addressing large-area change mapping, especially in an operational context (Dobson and Bright 1994;

Loveland et al. 2002). Thus, in light of the exciting potential for future operational land cover monitoring programs, and in acknowledgement of the large amount of new, disparate methods currently employed in change detection studies in the literature, this chapter presents a review of the key requirements and chief challenges of land cover change monitoring.

A general classification of the spatial resolution of remote sensing platforms produces three categories (Rogan and Chen 2004): (1) coarse resolution (≥250 m) (e.g., Advanced Very High Resolution Radiometer [AVHRR]); (2) medium resolution (<250 m but ≥20 m) (e.g., Landsat Multispectral Scanner [MSS]); and (3) fine resolution (<20 m) (e.g., WorldView-2).

21.2 Land Cover Change Detection and Monitoring: Theory and Practice

Figure 21.1 presents a conceptual scheme of a forest environment and demonstrates that land cover change can result in alterations (increase or decrease) in the abundance, composition, and condition of remote sensing scene elements over various spatial and temporal resolutions (Stow et al. 1990). Conversion is shown in Figure 21.1b. In contrast, modification (Figure 21.1c and d) involves maintenance of the existing cover type in the face of changes to its scene elements (i.e., change in abundance and condition).

Detection and monitoring land cover change across large areas are two of the most important tasks that remote sensing data and technology can accomplish (Woodcock et al. 2001). Land cover change detection, one of the most common uses of remotely sensed data, is possible when changes in the surface phenomena of interest result in detectable changes in radiance, emittance (Lunetta and Elvidge 1998), Light Detection and Ranging (LIDAR) return values (Wulder et al. 2007), or microwave backscatter values (Rignot and Vanzyl 1993; Grover et al. 1999), which implicitly involves spatial patterns of change (Crews-Meyer 2002).

Khorram et al. (1999) explored the spatial context of land cover change and stated that spatial entities either (1) become a different category; (2) expand, shrink, or change shape; (3) shift position; or (4) fragment or coalesce. These concepts are well understood by remote sensing practitioners, and especially the resource management community, worldwide, but less so by ecology, sociology, and vulnerability communities.

However, in the last 10 years, a number of important developments have occurred that have helped improve the adoption of land change information by scientific communities that had not done so previously. Land change science (Turner et al. 2007) has emerged as an interdisciplinary field that seeks to understand LCLU dynamics as a coupled human–environment system. This burgeoning theoretical field claims Earth observation data as a crucial component and so has effectively exposed land cover mapping and monitoring practices to a broad audience of anthropologists, economists, and sociologists. Another important development is the opening of the Landsat archive in 2008

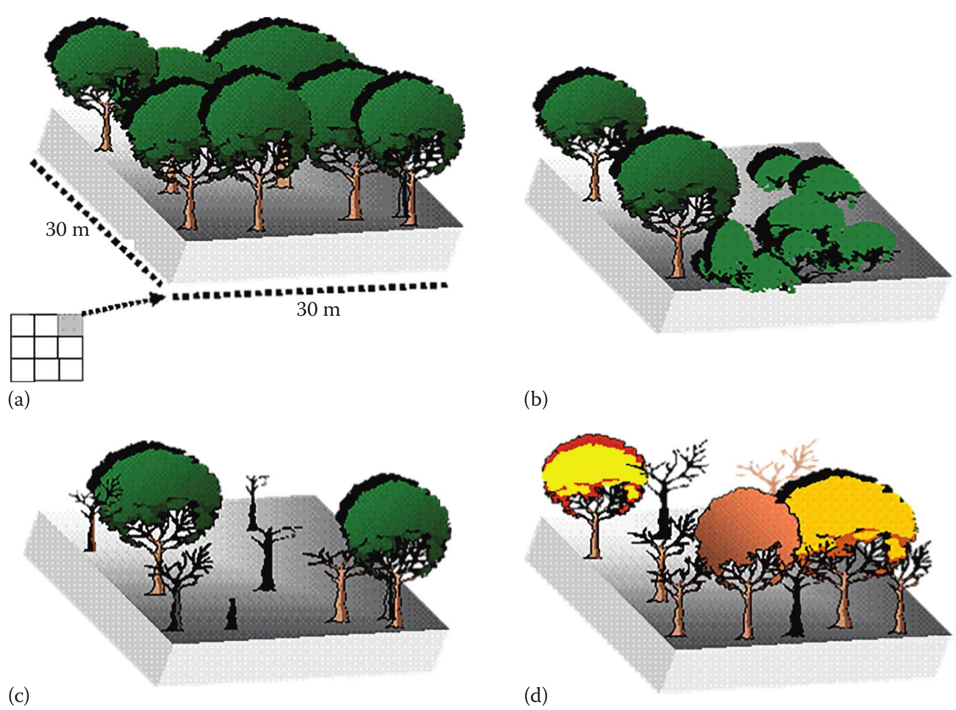

FIGURE 21.1 Conceptual scheme representing land-cover changes from Time 1 (represented by (a)) to Time 2 (represented by (b), (c), and/or (d)): (b) change in composition; (c) change in abundance; and (d) change in condition, of vegetation cover, which influence the spectral quantity and quality of solar reflected radiation received by a Landsat sensor (30 m pixel).

(Wulder et al. 2012). The availability of dense time series of moderate spatial resolution Landsat imagery (since 1972 to present) has already had significant impacts on the ecology community (Kennedy et al. 2014) as temporal sequences and trajectories of importance to ecological conservation are now mostly matched by Landsat time stacks. Overall, therefore, we can expect to see, in the near future, remotely sensed data being used to test or verify theories in a much broader array of disciplines than ever before.

Most terrestrial surfaces are comprised complex configurations of land cover attributes (Turner et al. 1999). These range from being mainly *natural* to those that are largely human dominated (Turner and Dale 1991). Land cover change is viewed in terms of modifications in component attributes within either natural or human-dominated land cover or conversions from natural to human-dominated land cover (Lambin et al. 1999). Despite the recognized importance of land cover modifications (e.g., wind or insect damage), and in contrast to conversions (i.e., forest loss due to agriculture gain), they are not as well documented at operational scales (Lambin et al. 2001). This is partly due to the fact that modifications occur at many different spatial scales and are often too subtle and cryptic to be mapped with a high level of confidence (Ekstrand 1990; Gong and Xu 2003). Therefore, land cover modification analysis requires that a greater level of detail be accommodated in remote sensing analysis.

Macleod and Congalton (1998) listed four aspects of change detection that are important when monitoring land cover using remote sensing data: (1) detecting changes that have occurred (Fung 1990; Lunetta et al. 2002), (2) identifying the nature of the change (Hayes and Sader 2001; Seto et al. 2002), (3) measuring the areal extent of the change (Stow et al. 1990; Rogan et al. 2003), and (4) assessing the spatial pattern of the change (Crews-Meyer 2002; Read 2003). Therefore, change monitoring initiatives/programs (i.e., both current and planned) should try to accommodate these four factors, in addition to appreciating the magnitude, duration, and rate of changes that can occur (Rogan and Chen 2004). Additionally, the burgeoning operational monitoring paradigm represents a shift away from the paradigm of the ubiquitous two-date *end-to-end* change detection approach (i.e., only two dates used in analysis), due to their greater temporal scope (Kasischke et al. 2004).

21.3 Trends in Land Cover Change Detection and Monitoring

21.3.1 Historical Trends: Eight Epochs

The history of land cover change mapping and monitoring has witnessed five distinct periods, determined by the evolution of remote sensor technology, and research needs, related to resource management mandates and various scientific research interests:

1. Early case studies (late 1970s) were exploratory and primarily focused on urban change detection (Todd 1977).
2. Research then shifted to case study applications (early mid-1980s) in natural environments, based on the needs of resource management agencies and the burgeoning interest in carbon sequestration (Singh 1989).
3. Successful applications and experience (mid–late 1990s) led to more widespread applications of remote sensing over large areas and using a wide variety of methods (Lambin and Strahler 1994).
4. Improved sensor technology facilitated the increased interest in less-researched fields, such as urban applications of remote sensing, the cryosphere, and coastal-ocean research (mid-1990s–present) (Rashed et al. 2001), and the new approach adopted by the Moderate-Resolution Imaging Spectroradiometer (MODIS) science team to provide image information products such as global land cover (Friedl et al. 2011). Large-area, high spatial resolution remote sensing became possible in 1994, when the U.S. government allowed civil commercial companies to market high spatial resolution satellite remote sensing data (i.e., 1 and 4 m spatial resolution) (Glackin 1998).
5. Today, a 40-year archive of Landsat imagery, a 22-year archive of AVHRR Global Inventory Modeling and Mapping Studies (GIMMS) normalized difference vegetation index (NDVI) data, and a 15-year archive of MODIS imagery and information products, coupled with an explosion in image time series research and increased automation, have made operational regional–global-scale land change monitoring a reality (Wulder and Coops 2014). Table 21.1 presents a comparison of AVHRR, MODIS, and Landsat data in terms of spatial

TABLE 21.1 Comparison of AVHRR, MODIS, and Landsat in Terms of Spatial and Temporal Resolution

Sensor/Program	Temporal Lineage	Temporal Resolution	Geographic Coverage	Spatial Resolution	Information Content	Information
AVHRR-GIMMS	1982–2012	Biweekly composites	Global	1/12° (8 km at the equator)	NDVI	http://glcf.umd.edu/data/gimms/
MODIS	1999–present	Daily and 8-day composites	Global	250, 500, 1000 m	Multispectral/biophysical products	http://modis.gsfc.nasa.gov/
Landsat	1972–present	16 days	Regional	30 m Global Land Survey global coverage: 1970, 1990, 2000, 2005, 2010	Multispectral	http://landsat.gsfc.nasa.gov/ http://landsat.usgs.gov/science_GLS.php

and temporal resolution. Clearly, the high temporal coverage AVHRR and MODIS data are optimal for regional–global analysis, but they can only provide this coverage at coarse spatial resolution. On the other hand, Landsat data are provided at much finer spatial scales (30 m) but are mostly limited to local–regional coverage. However, the Global Land Survey initiative provides global Landsat coverage for five dates between the early 1970s and 2010. Spatial resolution is a key-limiting factor in the ability of remote sensing imagery to resolve land cover and land cover change classes. This is because spatial scale exerts a strong influence on the ability to extract information from remotely sensed data sets and requires careful specification and analysis. As a result, the question of which remotely sensed data are appropriate for specific land cover change monitoring applications remains an open one. Obviously, the resolvability of land cover change increases with higher spatial resolution. However, high spatial resolution imagery is not typically needed to accurately detect general land cover changes (the goal of large-area monitoring studies) in most environments (Franklin and Wulder 2002). Studying a variety of environments, Townshend and Justice (1988) reported that spatial resolutions coarser than about 200 m undermined the reliable detection of land cover changes. Pax-Lenney and Woodcock (1997) examined the impact of coarsening the spatial resolution on the accuracy of areal estimates of agricultural fields in Egypt (30–120–240–480–960 m). Most of the coarse-resolution estimates were within 10% of the original 30 m estimates. Therefore, medium spatial resolution data remain the optimal choice for most land cover change studies, but more research over time will challenge this assertion in the interest of global-scale estimation and cost reduction, using coarse spatial resolution data, relative to the particular application.

21.3.2 Cause of Land Cover Change

A brief survey of the number of new remote sensing journals shows that 24 journals have been launched since 2007 (an increase of 60% in a 7-year time span). The remarkable proliferation of new journals likely reflects the growing user community and wealth of new remote sensing applications, enabled by a growing time series of free data and also the increased availability of open source software packages (e.g., Quantum GIS). Today, techniques to perform change detection have become numerous as a result of increasing versatility in manipulating digital data and growing computing power (Rogan and Chen 2004). The sheer number of published articles and the importance to resource management indicate both the degree to which remote sensing is used and the proliferation of methods employed. One dimension of this proliferation is progress in developing new and improved ways of detecting change, while another dimension is the wide variety of kinds of changes being monitored (Table 21.2). Table 21.2 presents the dominant causes of multitemporal land cover change in natural and human-dominated environments and their temporal and physical characteristics. Each change event can result in very different magnitude (i.e., small–large), duration (i.e., days to decades), and temporal rates (i.e., slow–fast) (Aldrich 1975; Gong and Xu 2003). Understanding the magnitude, duration, and rate of land cover disturbances has severe implications for the success of a land cover monitoring study because it permits researchers to determine the most appropriate sensor, derived data set, frequency of acquisition, level of image processing, and reproducible map legend.

It is important to note that not all land change disturbances are equally important in change detection studies, and not all disturbances may be detected as confidently as others (Gong and Xu 2003). For example, land changes of lesser concern to forest managers include those related to interannual variability and growth variation caused by climate variability, whereas, to global change modelers, the last type of change is of chief concern (Turner et al. 1999). A key issue in change detection is understanding how the types of change affect land cover and also how they interact with one another. For example, phenological vegetation change, which varies temporally across scales ranging from years to decades, often interacts with more temporally discrete changes, such as burn scar vegetation depletion and postfire regeneration (Rogan et al. 2002).

21.4 Land Cover Change Detection Approaches

21.4.1 Monotemporal Change Detection: Products for Real Time and Specific Disturbance Types

Numerous land change applications, using only a single image date (i.e., monotemporal change detection) (Coppin and Bauer 1996, p. 217), which focus on a specific change event, have successfully detected a variety of land cover disturbances. These disturbances include water stress (Running and Donner 1987; Running and Pierce 1990), wildfires (Patterson and Yool 1998; Rogan and Franklin 2001), forest thinning (Nilson et al. 2001), forest pest damage (Leckie et al. 1988; Vogelmann and Rock 1988; Joria and Ahearn 1991; Franklin et al. 1994), forest mortality (Ekstrand 1990), and the effects of pollution on vegetation vigor (Pitblado and Amiro 1982; Toutoubalina and Rees 1999).

Monotemporal applications are an effective application of "swapping time for space." Applications of remotely sensed data for disturbance-specific monitoring have considerable advantages, including savings in processing time and reduced costs (Patterson and Yool 1998). Further, end users may require a *quick look* at a particular disturbance for rapid response in the case of mudslide, wildfire, or flood events. A good example of this is the U.S. Forest Service rapid-response wildfire detection project that relies on MODIS active fire detection data (USFS 2004). However, monotemporal approaches rely heavily on assumptions

TABLE 21.2 Causes of Land Cover Change and Their Magnitude, Duration, and Rate

Cause	Magnitude	Duration	Rate	References
Phenology	Small–medium	Days–months	Medium	Goodin et al. (2002), Jakubauskas et al. (2002), Zhang et al (2003)
Regeneration	Small–medium	Days–decades	Slow	Fiorella and Ripple (1993), Lawrence and Ripple (2000)
Drought	Small–medium	Months–years	Slow	Peters et al. (1993), Jacobberger-Jellison (1994)
Flooding	Medium–large	Days–weeks	Medium–fast	Blasco et al. (1992), Michener and Houhoulis (1997), Rogan et al. (2001), Zhan et al. (2002)
Wildfire	Small–large	Days–weeks	Fast	Patterson and Yool (1998), Rogan and Yool (2000)
Disease	Small–large	Days–years	Slow–medium	Wilson et al. (2002), Kelly and Meentemeyer (2002)
Insect attack	Small–large	Days–years	Slow–fast	Muchoney and Haack (1994), Chalifoux et al. (1998), Radeloff et al. (1999)
Ice storm	Small–large	Years	Medium–fast	Dupigny-Giroux et al. (2002), Millward and Kraft (2004), Olthoff et al. (2004)
Mortality	Medium–large	Days–years	Slow–fast	Collins and Woodcock (1996), Allen and Kupfer (2000)
Water/nitrogen stress	Small–medium	Days–years	Slow–fast	Running and Donner (1987), Penuelas et al. (1994)
Pollution	Small–large	Years	Slow	Ekstrand (1994), Rock et al. (1988), Rees and Williams (1997), Diem (2002), Tommervik et al. (2003)
Thinning	Medium–large	Days	Fast	Olsson (1995), Nilson et al. (2001), Peddle et al. (2003a)
Clear-cutting	Large	Days	Fast	Hayes and Sader (2001)
Replanting	Small–medium	Days–decades	Fast	Coppin and Bauer (1996), Levien et al. (1999)
Mining	Large	Days–decades	Medium	Cadac (1998)
Grazing	Small–medium	Days–decades	Slow–medium	Rees et al. (2003)
Wind throw	Large	Days	Medium–fast	Mukai and Hasegawa (2000), Kundu et al. (2001), Lindemann and Baker (2002)
Erosion	Small–medium	Days–weeks	Fast	Dwivedi et al. (1997), Hong and Iisaka (1987), Michalek et al. (1993), Rosin and Hervas (2002)
Environmental quality	Small–large	Months–years	Slow	Fung and Siu (2000)
Fragmentation	Small–large	Days	Fast	Wickham et al. (1999), Millington et al. (2003)
Conversion	Large	Years–decades	Slow–medium	Jha and Unni (1994), Loveland et al. (2002)
Desertification	Small	Years–decades	Slow	Robinove et al. (1981), Pilon et al. (1988)

Source: After Gong and Xu (2003).

about the initial state of land cover in the particular study area (Ekstrand 1994). Indeed, an important factor in the success of these studies is that prechange information (e.g., predisturbance spectral information) and stand and landscape characteristics (e.g., stratification of mixed vegetation canopies, stand-based analysis, slope, and aspect) are controlled to minimize confusion between change and unchanged land cover types (Ekstrand 1990). This implies that prechange, or predisturbance spectral, and/or land cover information are needed to robustly resolve monotemporal disturbances using remotely sensed data (Franklin 2001). For monotemporal (rapid response) applications, coarse spatial resolution data acquired by sensors such as AVHRR, Satellite Pour l'Observation de la Terre (SPOT) Vegetation, and MODIS data are appropriate. Image preprocessing requirements are minimal, but a spectral transformation (e.g., vegetation index) would be useful to separate the disturbance signal (e.g., wildfire or flooding) from the undisturbed background and facilitate simple spectral change thresholding, if required.

Recent advances in real-time disaster response management provide an informative application of monotemporal change detection. The International Charter on Space and Major Disasters (http://www.disasterscharter.org) was founded in 1999, after the catastrophic Hurricane Mitch struck Central America. The Charter aims at providing a unified system of space data acquisition and delivery to locations affected by natural disasters and receives imagery contributions from a group of 15 international participating Earth observation agencies. Additionally, the United Nations Platform for Space-based Information for Disaster Management and Emergency Response (UN-SPIDER program) was established in 2006 to serve as a gateway to space information for disaster management support (http://www.un-spider.org/). These two disaster response programs rely on high spatial resolution data to achieve their goals.

While high spatial resolution sensors cannot conveniently or cost effectively provide wall-to-wall coverage for large-area change mapping applications due to data cost and volume, they are invaluable as a source of ground reference information for medium- and coarse-resolution products/applications and for operational monitoring studies over small spatial extents (Stow et al. 2002). Technological advances in sensor design allow aerial photographic precision and quality in these satellite-based data and permit the investigation of thematic information at the highest order in both natural and urban/suburban landscapes. Though promising, change detection using high spatial resolution data requires further research and development (Rogan and Chen 2004). Data costs, compared to free Landsat data, for example, are very high. Other issues include the impact of off-nadir view angles on change detection and the increasing need for object-based mapping (Stow et al. 2004). Further, geometric distortion is a vexing problem for most airborne data sets (see Franklin and Wulder 2002).

21.4.2 Bitemporal Change Detection: Map Comparison and Disturbance Analysis

In the vast majority of land cover change studies, imagery from one date is compared to another date. Within this paradigm of analyzing images as *endpoints*, there has been a tremendous variety of methods developed and used. This proclivity of bitemporal studies has been caused by several factors: (1) There are fewer data to analyze, (2) studies have been conducted to satisfy burgeoning short-term resource management needs, (3) various researchers have needed a straightforward scenario in order to compare and evaluate a variety of change detection techniques to find an optimal method, (4) most studies have been conducted in regions of limited spatial extent and landscape heterogeneity, and (5) these studies have focused on a single disturbance event (e.g., flooding, fire, logging, or pest infestation) in environmentally (e.g., tropical forests) or politically (e.g., municipalities) important regions. Thus, while bitemporal change detection will continue to serve its purpose for a long time to come, its efficiency and consistency over large, heterogeneous areas has yet to be fully examined (Rogan et al. 2003). However, the potential for moderate spatial resolution analysis in land change monitoring is enormous (Zhu and Woodcock 2013).

21.4.2.1 Bitemporal Change Detection Methods

The selection of an appropriate change detection technique depends on the information requirements, data availability and quality, time and cost constraints, analysis skill, and experience (Johnson and Kasischke 1998). Table 21.3 presents a summary of a variety of land cover change detection methods and their advantages and disadvantages for operational monitoring. Twelve change detection methods are compared according to their status in terms of operational use, as well as their relative strengths and weaknesses. The chief division between the 12 methods occurs between postclassification comparison (i.e., categorical change) and the suite of existing continuous change detection techniques (e.g., image differencing).

The choice of either categorical or continuous comparison must be based on an understanding of the spectral and spatial impact of a given land cover disturbance or range of disturbances. If land cover attributes are expected to change category (e.g., forest to urban), then postclassification comparison is suitable, if not optimal. However, in many ecosystems, complete land cover conversion rarely occurs over short time intervals (i.e., 3–5 years). In effect, modification in condition and abundance is more common than conversion (Coppin and Bauer 1994; Rogan et al. 2002). Therefore, this makes continuous comparison a more suitable choice of change detection approach for monitoring land cover modifications, especially over relatively short time intervals (i.e., 2–5 years). When longer time periods are considered (e.g., 5–10 years), then categorical comparison may be more suitable, as actual land cover conversion may be more likely to occur. In situations where digital data are not available for earlier time periods (e.g., pre-1972), categorical comparison is the only feasible approach (e.g., a land cover map of 1775 can be compared to a 1990 land cover map) (Petit and Lambin 2002).

21.4.2.2 Map-Updating Approaches

Another interesting trend in bitemporal change mapping is the use of novel map-updating approaches. Postclassification comparison has been implemented in hundreds of land change case studies, but it is problematic in many land change monitoring scenarios (Stow et al. 1980). Over large areas, land change mapping is challenging for some of the following reasons: (1) Data issues such as cost, platform continuity, availability of aerial photographs, or in situ data inhibit comprehensive spatial and temporal coverage and (2) cloud cover, nonstationarity in landscape features, and phenological variability further limit the usability of available imagery. In combination, these challenges make the task of remapping an entire landscape for a second or even third iteration very expensive and possibly unachievable at an acceptable level of map accuracy (Rogan and Chen 2004). Actual land change due to categorical conversions (e.g., forest to urban) or within-category modifications (e.g., timber harvest) usually occupies only a small portion of a pair of 34,000 km^2 Landsat images (e.g., less than 20%) (Rogan et al. 2003) such that independent remapping of a landscape for a new time period is not warranted as long as there are no drastic changes to a land monitoring protocol (e.g., new map legend, change to incompatible new data sources) (Rogan and Chen 2004).

There are two main methods of map updating present in the remote sensing literature: (1) human-interpreted delineation of new changes using multitemporal data and (2) digital change detection of multitemporal imagery to detect a specific type of disturbance, such as urban sprawl, or forest damage. Feranec et al. (2007) implemented a human-interpretation method of change detection with visually interpreted aerial photography to update the CORINE 44 category land cover map for 1990 and 2000. The 2000 land cover map was created by visually and manually editing polygons of change in the original 1990 classification with overall accuracy above 85%. Other studies have used more automated methods of predating and postdating land cover maps to monitor forest change. Wulder et al. (2008) implemented a technique to postdate a 2000 land cover map to 2003 land cover conditions to detect forest clear-cuts using the near-infrared band from Landsat TM/Enhanced Thematic Mapper+ (ETM+), SPOT-4, and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) data. Forest clear-cuts were detected using an ordinal ranking method that assigns pixels a value based on its reflectance relative to all other pixels. Detected clear-cuts were integrated into the preexisting 2000 EOSD eight-category land cover product. We expect that new innovative approaches to map updating will emerge in the next decade as remote sensing practitioners merge change mapping and resource inventory in a mutually beneficial process.

TABLE 21.3 Summary of a Variety of Land Cover Change Detection Methods and Their Advantages and Disadvantages for Operational Monitoring

Change Detection Method and Status[a]	Advantages	Disadvantages
Postclassification comparison (PCC)	Provides detailed *from–to* information	Only complete class changes are detected
status = I	Can be used with different sensors and with different spatial and spectral resolutions	Heavily dependent on the accuracy of input maps and consistency between mapping methods
	Permits the use of data with interdate phenological differences	Costs often prohibitive over large areas
	Less sensitive to radiometric/geometric errors	
Composite analysis (CA)	Requires only a single classification	Can require a large number of classes and a large calibration data set
Status = I	Can be applied to both raw and enhanced data (e.g., vegetation indices, albedo)	Separation of spectral changes from temporal changes can be difficult
	Makes effective use of prechange (reference) image	
Image differencing (ID)	Can be applied to both raw and enhanced data	Requires optimization of change/no change threshold
status = I	Provides detailed information on “within class change”	Difference image interpretation can be difficult
		Cannot differentiate spectral differences resulting from different original spectral values
		Highly sensitive to radiometric/geometric errors
		Does not provide *from–to* information
Image ratioing (IR)	Can be applied to both raw and enhanced data	Highly sensitive to radiometric/geometric errors
status = I	Can mitigate atmospheric and sun angle effects	Threshold optimization can be difficult, as change is nonlinearly represented
Change vector analysis (CVA)	Can be applied to both raw and enhanced data	Highly sensitive to radiometric/geometric errors
status = F	Provides detailed *from–to* information	Change-direction outputs are difficult to interpret with a large number of input bands
		Change magnitude thresholding is subjective
Multitemporal Kauth Thomas (MKT)	Results are intuitive	Coefficients are sensor dependent
status = I	Produces suites of change, no change, and noise features	Highly sensitive to radiometric/geometric errors
	Standardized coefficients permit application and comparison over time and space	
Multitemporal spectral mixture analysis (MSMA)	Results are intuitive (biophysically)	Sensitive to choice of end-member type
	Can be used to compare fraction estimates across different sensors and platforms	
Principal components analysis (PCA)	Can be applied to both single-date, composite multidate, and composite ID data	Components can be difficult to interpret
status = I	Reduces multispectral data sets into features representing change, no change, and noise	Threshold optimization can be difficult
	In multitemporal analysis, standardized components can minimize atmospheric and sun angle differences	Statistically based, so limited in space and time
		Sensitive to disproportionate amounts of variance in the imagery
Multivariate alteration detection (MAD)	Reduces multispectral data sets into features representing change, no change, and noise	Has not been widely used
status = E	Can be used to compare information from different sensors	
	Insensitive to disproportionate amounts of variance in imagery	
Multitemporal visualization	Simple and intuitive	Qualitative
status = I	Permits inspection of three dates of imagery as RGB	Does not provide *from–to* information
Knowledge-based approaches	Automatic detection of change	Complicated approach to develop
status = F		Have not been widely used
Cross-correlation analysis (CCA)	Allows for direct updating of land cover maps	Has not been widely used
status = F		

[a] Status of the method in an operational context for land cover change monitoring: I, implemented in operational context; F, feasible in an operational context; E, experimental.

21.4.3 Temporal Trend Analysis: Automation and Big Data

Over the last four decades, voluminous amounts of digital data have been gathered from an ever growing number of satellites and sensors continuously monitoring the Earth, atmosphere, and oceans. Fortunately, the massive increase in available data has coincided with a rise in computing power, and since the widespread popularization of online mapping platforms and user-generated geographic information, often linked to the release of Google Earth™ in 2005, a broader user base for the "Geoweb" has developed (Elwood 2011). The most significant change in the practice of land cover change mapping and monitoring has come from this "Big Data" paradigm, also known as "data-intensive science" (Kelling et al. 2009).

21.4.3.1 Hypertemporal Remote Sensing Data in Trend Analysis

Trend, or temporal trajectory, analysis involves the application of data acquired on a large number of observation dates (i.e., hypertemporal) (inter- and intra-annual), traditionally using coarse spatial resolution, spectrally transformed imagery (e.g., NDVI, photosynthetically active radiation, and leaf area index estimates derived from AVHRR and MODIS). This topic is reviewed thoroughly by Henebry and de Beurs (2013). Once assembled, temporal–spectral profiles can be useful for describing high-frequency land cover modifications over coarse spatial scales (Eastman et al. 2009). The study of land surface phenology has witnessed a large increase in remote sensing practitioners and applications as a method for studying the patterns of plant and animal growth cycles, due to the increase in freely available information/data sets. Phenological events are sensitive to climate variation such that phenology data provide timely baseline information for documenting trends in agriculture, irrigation, and forest growth rates and detecting the impacts of climate change on multiple scales (Henebry and de Beurs 2013). The increased complexity that remote sensing practitioners face when working with hypertemporal data sets is now being ameliorated through new software functionality. For example, the Earth Trends Modeler is an integrated suite of tools within IDRISI software for the analysis of image time series data and allows the user to perform and analyze trend analysis results in both graphic and cartographic format (http://www.clarklabs.org/).

Information from trend analysis can provide information on landscape or land surface phenological variability for finer spatial resolution studies so that change related to disturbances can be potentially separated from climate (temperature and precipitation) variability (Borak et al. 2000). High temporal, coarse spatial resolution imagery has also been used effectively to document the prevailing trends in vegetation phenology over large areas to guide the acquisition of medium spatial resolution imagery (i.e., to reduce commission errors caused by uneven intra- and interannual green up) (Rees et al. 2003). As such, changes inherently linked to seasonality can potentially be separated from other land cover changes (Coppin et al. 2002). However, spatial resolution is often a limiting factor in these studies, especially when examining subtle land cover changes (Rees et al. 2003).

21.4.3.2 Challenges of Trend Analysis

One of the most challenging aspects of trend analysis is that it requires a high level of image preprocessing to account for sensor and platform differences, sensor drift, etc. (Coppin et al. 2004). Trend analysis can be performed using coarse-to-medium spatial resolution data, although coarse-resolution data are more plentiful. Substantial preprocessing is required, given the large volume of data and the need for a high level of geometric and radiometric consistency. While classification is not essential, the use of image transformations to reduce data volume in size is essential. Most large-area programs utilize categorical comparison approaches to detect and monitor land cover change. While this development is noteworthy, and expected to continue, the land change science community requires information on land cover modifications, which conversion-focused programs cannot efficiently or reliably provide. However, there is potential for improvement with increased data availability and accessibility and growing experience with and understanding of sensors and imagery in large-area scenarios (Franklin 2001; Rogan and Chen 2004).

21.4.3.3 Medium-Resolution Data for Trend Analysis

A very promising new development is the advancement of data fusion, which involves the blending of multiple colocated images to produce a hybrid information product that minimizes the limitations of each contributing data set (Walker et al. 2012). A typical fusion combination merges low temporal/high spatial resolution data with high temporal/low spatial resolution data methods to extend the temporal profile of Landsat data using daily or 8-day MODIS reflectance data (Gao et al. 2006).

Medium spatial resolution data sources are considered optimal to obtain sufficient thematic detail for large-area monitoring applications. Fortunately, the last decade has witnessed the growth in availability of medium spatial resolution data sets such as the Web-Enabled Landsat Data (WELD) program (Roy et al. 2010). Since January 2008, the USGS survey has been providing free terrain-corrected and radiometrically calibrated Landsat data via the Internet. The WELD system is being expanded to the global scale to provide monthly and annual Landsat 30 m information for any terrestrial non-Antarctic location for six 3-year epochs spaced every 5 years from 1985 to 2010. The WELD products are developed specifically to provide consistent data that can be used to derive land cover as well as biophysical products for assessment of land surface dynamics (Roy et al. 2010).

21.4.4 Comparison of Several Automated Change Detection Approaches

In recent years, much attention has been focused on automating the detection of land cover change, specifically forest disturbance, across broad landscapes, and using dense image time series stacks.

TABLE 21.4 Comparison of Seven Prominent Change Detection Algorithms according to Ease of Use, Computation Time, Data Type, and Functionality

Algorithms	Ease of Use	Computation Time	Data Type	Cost	Available to Use	Highlights Deforestation	Highlights Degradation	Source
DI	2	NA	L	Free	Y	Y	N	Healey et al. (2005)
DI′	2	NA	L	Free	Y	Y	Y	Hais et al. (2009)
CLASlite	1	1	L,S,A,M	Free	Y—with permission	Y	Y	Asner et al. (2009)
VCT	2	1	L,S,IRS	Free	Y	Y	Y	Huang et al. (2010)
LandTrendr	3	3	L	Free	Y—requires ENVI	Y	Y	Kennedy et al. (2010)
MGDI	1	NA	M	Free	N	Y	N	Mildrexler et al. (2009)
STAARCH	3	NA	L,M	Free	Y	Y	Y	Hilker et al. (2009)

DI, disturbance index; DI′, disturbance index prime; MGDI, MODIS Global Disturbance Index; CLASlite, Carnegie Landsat Analysis System Lite; VCT, Vegetation Change Tracker; LandTrendr, Landsat-based Detection of Trends in Disturbance and Recovery; STAARCH, Spatial Temporal Adaptive Algorithm for mapping Reflectance Change; NA, not available; L, Landsat 4 and 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+); S, Satellite Pour l'Observation de la Terre 4 and 5 (SPOT); A, Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER); Moderate Resolution Imaging Spectrometer (MODIS); IRS, Indian Remote Sensing Satellite; ENVI, Exelis Visual Information Solutions.

Many spectral disturbance indices (DIs) (Healey et al. 2005; Hais et al. 2009; Mildrexler et al. 2009) and software platforms (Asner et al. 2009; Hilker et al. 2009; Huang et al. 2010; Kennedy et al. 2010) have been created to monitor forest disturbance, each with their own relative strengths and weaknesses (Table 21.4).

21.4.4.1 Disturbance Index

Healey et al. (2005) developed a novel combination of the Tasseled Cap features (brightness [B], greenness [G], and wetness [W]) to highlight forest disturbances over single and multidate Landsat image time series, known as the DI. The DI is a linear combination of the B, G, and W features where each feature is rescaled to one standard deviation above or below the mean forest value of the landscape under investigation, resulting in the equation

$$DI = B_r - (G_r + W_r)$$

where r indicates the rescaled features. The DI is most sensitive to stand-replacing, discrete disturbances, which create a strong, stable, and relatively predictable spectral signal across space and time. Alternatively, the DI is less robust in landscapes where rapid postdisturbance succession occurs, such that the disturbance signal is weakened by increased understory vegetation growth and heterogeneity.

21.4.4.2 Disturbance Index′

Hais et al. (2009) refined the DI to account for gradual disturbances across landscapes and forest stands exhibiting rapid succession (i.e., increased greenness) in understory vegetation. The disturbance index′ (DI′) equation is as follows:

$$DI' = W_r - B_r$$

By removing the greenness band from the original DI equation, the DI′ showed a heightened sensitivity to both discrete (i.e., clear-cut, windthrow, avalanche) and gradual disturbances (i.e., defoliation, insect mortality) across space and time when compared to the DI, G, B, W, and the normalized difference wetness index (NDWI).

21.4.4.2.1 MODIS Global Disturbance Index

The MODIS Global Disturbance Index (MGDI; Mildrexler et al. 2009) is an automated change detection algorithm, which fuses the MODIS Reflectance product, Land Surface Temperature (LST), and MODIS enhanced vegetation index (EVI) data to detect large-area forest disturbances at global, continental, and subcontinental scales. The MGDI uses annual maximum LST composites to detect large changes in land-surface energy and links those changes to the EVI signal, thus detecting discrete disturbances. Due to the scales at which the algorithm is optimized for, disturbances such as wildland fire events, hurricane damage, large-scale windthrow, clear-cuts, and land clearing for agriculture will be the major landscape modifiers captured over the time series.

21.4.4.3 CLASlite

Carnegie Landsat Analysis System–Lite (CLASlite) (V 3.1) is a stand-alone, fully automated software package used to map forest cover, deforestation, and forest degradation over broad spatial extents and long time series by experts and nonexperts alike (Asner et al. 2009). CLASlite boasts a 1 h processing time on a standard Windows PC for a 30 m spatial resolution image across 10,000 km^2. CLASlite enables users to input raw data from a variety of satellite platforms (Landsat 4, 5, 7, 8; ASTER; Advanced Land Imager [ALI]; SPOT 4, 5; MODIS) where an automation procedure atmospherically corrects, cloud masks, and classifies images across multiple dates with little user input (see Asner et al. 2009 for more details). The CLASlite algorithm utilizes a spectral mixture procedure called Automated Monte Carlo Unmixing (AutoMCU) to classify forest/nonforested areas for one or multiple image dates. Although the spectral libraries used in this procedure are optimized for tropical forests (>300,000 spectral signatures), it has also been shown to classify temperate forests with great success (see case study in the following text).

21.4.4.4 Vegetation Change Tracker

The vegetation change tracker (VCT) (Huang et al. 2010) is an automated algorithm used to delineate forest change across 12 or more Landsat time series stacks with little to no user parameterization for closed or near closed forest canopies. The VCT algorithm will automatically create initial masks (i.e., clouds, cloud shadows, water) and temporally normalize for all scenes, calculate forest features, temporally interpolate masked land areas, and create a composite output image of all locations that experienced a disturbance for each time step. Additionally, the VCT algorithm calculates multiple types of change magnitude measures and tracks postdisturbance vegetation processes (i.e., succession). The VCT disturbance mapping technique is ideal for discrete, land-clearing events but works poorly for nonstand clearing events (i.e., thinning, selective logging, insect outbreak).

21.4.4.5 LandTrendr

The Landsat-based Detection of Trends in Disturbance and Recovery (LandTrendr; Kennedy et al. 2010) is an algorithm that enables the user to systematically analyze a dense Landsat time series stack to produce robust short-term disturbance and long-term vegetation trend maps. Users are able to provide dense Landsat time series stacks into the LandTrendr, which are atmospherically corrected (Cos(t) algorithm), masked (smoke, cloud, cloud shadow, water), and temporally segmented as a means to capture landscape disturbances. Output images and figures provide a wealth of information that quantify landscape dynamics over the time series stack, allowing for a much more detailed assessment than bitemporal change methods can provide.

21.4.4.6 Spatial Temporal Adaptive Algorithm for Mapping Reflectance Change

The Spatial Temporal Adaptive Algorithm for Mapping Reflectance Change (STAARCH; Hikler et al. 2009) blends Landsat and MODIS data to enhance the temporal resolution of Landsat (16 days) to MODIS (8 days). The STAARCH model employs Healey et al.'s (2005) DI to detect landscape changes, where the DI calculation is completely automated. To aid in heterogeneous landscapes, the STAARCH model uses the minimum standard deviation of forest spectral values to increase the sensitivity of the DI to spectral forest change (i.e., disturbance). Additionally, this algorithm is able to create synthetic Landsat images for a given study area/period for each available MODIS scene used. To note, this algorithm builds upon and improves the performance of the Spatial and Temporal Adaptive Reflectance Fusion Model (STARFM) algorithm (Gao et al. 2006).

21.4.4.7 Summary and Comparison of Automated Change Methods

To summarize the aforementioned change detection indices and algorithms, it is necessary to evaluate their purposes accordingly (Tables 21.4 and 21.5). For high spatial and temporal resolution rapid change detection, it would be most advantageous to employ the CLASlite or the VCT algorithm. To evaluate longer-term environmental landscape dynamics, where computational power and time are not limiting, the LandTrendr would be the most appropriate algorithm of choice. The two DIs (DI and DI′) would be most efficiently utilized under the conditions where forest change detection across time would benefit from manual preprocessing steps to accommodate multidate disparities. Additionally, the MGDI would allow for a more sophisticated approximation of landscape disturbances across a very large area. Lastly, the STAARCH algorithm not only allows for a highly accurate downscaling of MODIS to Landsat pixel scale but also accommodates an automated DI calculation; therefore, this would be the algorithm of choice if large spatial extents combined with a need for high spatial and temporal resolution is necessary. It is imperative to assess each change detection algorithm based on their strengths, weakness, and best fit for the research objectives and scales (both spatially and temporally).

TABLE 21.5 Comparison of Seven Prominent Change Detection Algorithms according to the Degree of Automation with respect to Atmospheric Correction, Cloud Masking, Image Calibration, and Mosaicking

Algorithms	Atmospheric Correction	Cloud Mask	Calibration	Mosaic Multiimage
DI	N	N	Y	N
DI′	N	N	Y	N
MGDI	N	N	Y	Y
CLASlite	Y—6S	Y	Y	N
VCT	Y—LEDAPS	Y	Y	N
LandTrendr	Y—Cos(t)	Y	Y	Y
STAARCH	N	Y	Y	N

DI, disturbance index; DI′, disturbance index prime; MGDI, MODIS Global Disturbance Index; CLASlite, Carnegie Landsat Analysis System Lite; VCT, Vegetation Change Tracker; LandTrendr, Landsat-based Detection of Trends in Disturbance and Recovery; STAARCH, Spatial Temporal Adaptive Algorithm for Mapping Reflectance Change; LEDAPS, Landsat Ecosystem Disturbance Adaptive Processing System; Cos(t), cosine of theta.

21.5 Accuracy Assessment: Beyond Statistics

"It is extremely difficult to implement a consistent, comprehensive, quantitative accuracy assessment for large-area change maps" (Loveland et al. 2002, p. 1094). Following the detection and classification/mapping of land cover change, it is preferable that the accuracy of the change maps be assessed. This topic is reviewed in detail by Olofsson et al. (2014). Accuracy assessment serves as a guide to the map quality and to reveal uncertainty and its likely implications to the end user. Accuracy assessment for change detection studies is more challenging than for single-date studies (Congalton 1991; Khorram et al. 1999). This is because change classes usually represent a very small portion of the change image, or thematic map. Additionally, when performing retrospective change detection, acquiring an adequate database of historical reference materials, such as historic aerial photographs, can be very difficult, if not impossible (Biging et al. 1998). The provision of archived imagery by Google Earth provides an important component to addressing the more vexing concerns in land change accuracy assessment (Dorais and Cardille 2011). Unfortunately, the remote sensing community has tended to focus exclusively on the calculation of map accuracy/validation statistics to demonstrate the validity of a method or the worth of a land cover map (Rogan and Chen 2004). While having statistical information about map accuracy is very useful, it ignores many other facets of a change map that are vital to making sure that true change has been captured (Ghimere et al. 2010). These important facets include estimating the potential outcome of the mapping exercise, estimating the areal dominance of categories, and determining the desired shape, location, association, and configuration of mapped categories.

Based on 10 years of experience mapping forest, wetland, and urban change in Massachusetts, the Massachusetts Forest Monitoring Program (MaFoMP) (Rogan et al. 2010) developed the following list of eight steps to pursue when mapping change over a 40-year time period using all available cloud-free Landsat MSS, TM, and ETM+ imagery:

Step 1—Determine optimal data needs, image processing steps based on scene model (Strahler at al. 1986; Phinn et al. 2000), and desired map legend (e.g., Anderson et al. 1976).

Step 2—Determine optimal response design, support size, and sampling design (identify the trade-offs between support size and cost-logistical feasibility) (see Olofsson et al. 2014 for more details).

Step 3—Qualitatively estimate success of mapping project based on previous experience and literature (e.g., expected outcomes—"last time we achieved 80% overall accuracy").

Step 4—Estimate expected category area/dominance using maps from other sources or your knowledge of the study area (e.g., categories A and B should comprise over 70% of the study area, whereas categories C and D should comprise less than 2% of the study area).

Step 5—Estimate expected category shape, location, association, and configuration (e.g., categories F and G will fall only on the coast in long linear strips, associated with ocean water).

Step 6—Quantitatively estimate overall accuracy and per-class accuracy using validation data (should be appropriate support and sampling design). For a general purpose map, all categories should be ranked equal in importance (thus a balance must be struck between omission and commission errors) such that per-class accuracy should be equal. For a phenomenon-specific map (e.g., forest loss), certain categories should be ranked higher in importance than others such that omission errors should be avoided at all allowable costs, whereas certain levels of commission error are permissible (e.g., it is more important not to miss a rare category than it is to falsely map it). Keep in mind that resubstitution accuracy (i.e., using calibration data as validation data) can be a reasonable first-cut measure of your potential mapping success (Rogan et al. 2003).

Step 7—Engage in postclassification editing/filtering to achieve a product that *looks right*. This may make you return to your original training data and redo the work, especially in heterogeneous locations.

Step 8—Evaluate the map such that the end user can employ it wisely for a task that you may not have thought of (e.g., let the map user know your decisions/activities for Steps 1–8 earlier).

21.6 Massachusetts Case Study: CLASlite

This case study explores the application of CLASlite (Asner et al. 2009) mapping and disturbance detection software to map forest and forest change in Massachusetts. CLASlite can operate with a variety of satellite data types, including Landsat, SPOT, ASTER, ALI, and MODIS. Landsat TM, ETM+, and Operational Land Imager–Thermal Infrared Sensor (OLI-TIRS) data were acquired for 9 individual years spanning nearly three decades (Table 21.6) across eastern Massachusetts (Figure 21.2). Four Landsat tiles were downloaded for each respective year and georeferenced using image-to-image registration to an existing orthorectified Landsat image (http://www.landsat.org). All images were registered to an average root-mean-square error of less than one pixel.

Following the manual coregistration procedure, each scene was processed for each of the 9 years using CLASlite (Version 3.1; Asner et al., 2009). CLASlite is an automated change detection and mapping software optimized for tropical forests but was used here to test the feasibility across spatially heterogeneous temperate forested landscapes such as Massachusetts. CLASlite requires limited user interaction in the four main processing steps (image calibration, fraction image creation, forest cover mapping, and deforestation and disturbance delineation), which is optimal for rapid forest cover mapping spanning multiple dates.

TABLE 21.6 Detailed Description of Scene Date, Spatial Location, and Sensor Type Used

Acquisition Date	Landsat Scene Path	Landsat Scene Row	Landsat Sensor
August 8, 1985	12	30	TM
August 8, 1985	12	31	TM
September 1, 1985	13	30	TM
September 1, 1985	13	31	TM
August 15, 1993	12	30	TM
August 15, 1993	12	31	TM
July 5, 1993	13	30	TM
July 5, 1993	13	31	TM
August 21, 1995	12	30	TM
August 21, 1995	12	31	TM
July 15, 1999	13	30	TM
July 15, 1999	13	31	TM
July 31, 1999	12	30	ETM+
July 31, 1999	12	31	ETM+
July 23, 2002	12	30	TM
July 23, 2002	12	31	TM
July 10, 2009	12	30	TM
July 10, 2009	12	31	TM
August 18, 2009	13	30	TM
August 18, 2009	13	31	TM
August 30, 2010	12	30	TM
August 30, 2010	12	31	TM
September 6, 2010	13	30	TM
September 6, 2010	13	31	TM
July 17, 2011	12	30	TM
July 17, 2011	12	31	TM
June 16, 2011	13	30	TM
July 7, 2011	13	31	TM
August 6, 2013	12	30	OLI TIRS
August 6, 2013	12	31	OLI TIRS
September 30, 2013	13	30	OLI TIRS
September 30, 2013	13	31	OLI TIRS

First, all scenes were individually imported into CLASlite by specifying the required ancillary and metadata information. During image calibration, CLASlite uses 6S radiative transfer code to atmospherically correct each scene and convert the output images from radiance values to reflectance. Second, CLASlite employs a Monte Carlo (AutoMCU; Asner et al. 2002) spectral decomposition algorithm to partition each scene into proportional fractional cover types of bare ground (B), photosynthetic vegetation (PV), and nonphotosynthetic vegetation (NPV) for every pixel (Figure 21.2). During this stage, the user is able to specify the degree to which clouds and water bodies are masked out of the resulting image. Third, CLASlite delineates forest versus nonforest pixels based on a user-defined threshold based on proportional PV against B and NPV constituents (Figure 21.3). Finally, CLASlite evaluates the fractional and reflectance images to produce disturbance and degradation classifications for each time step. As defined by Asner et al. (2009), deforestation refers to a diffuse thinning of the forest canopy, while degradation quantifies any spatial or temporal persistence of forest disturbance. In this case study, CLASlite maps the location of deforestation and forest disturbance in eight eras: 1985–1993, 1993–1995, 1995–1999, 1999–2002, 2002–2009, 2009–2010, 2010–2011, and 2011–2013 (Figure 21.4).

CLASlite forest cover maps for each time period were validated using two independent approaches. The first method employed the 30 m resolution MaFoMP land cover maps (Rogan et al. 2010) for the years 1984, 1990, 2000, and 2009 to produce a cross tabulation matrix of quantity agreement and allocation agreement with the associated CLASlite forest cover images. This assessment determined the degree to which pixels of similar land cover type (forest or nonforest) are in agreement with the 30 m MaFoMP maps (MaFoMP 2011; Table 21.7). Errors of omission and commission were reported for each year as a percentage of all pixels in spatial and quantity agreement or disagreement to the MaFoMP map (Table 21.8). Kappa values and the Cramer's V statistic were reported for each year (Table 21.9).

Additionally, CLASlite change maps were validated using a randomly sampled collection of 200 classified pixels that were used to compare the CLASlite delineated pixel values to high spatial resolution Google Earth imagery (Dorais and Cardille 2011; Google, Inc. 2014). The second assessment allowed for an independent evaluation of quantity and allocation pixel agreement to determine the degree to which the CLASlite outputs are correctly classifying forest versus nonforest land cover types. We used available Google Earth imagery that was closest in temporal proximity to the CLASlite-generated forest cover maps. The original fine spatial resolution data were acquired from DigitalGlobe (i.e., WorldView-2 data). Additionally, the deforestation caused by the June 2011 tornado was validated via 50 randomly sampled points using a 2011 Google Earth image captured post tornado.

21.6.1 CLASlite Results

21.6.1.1 Forest Cover Mapping

Forest cover maps produced through an iterative thresholding procedure of the AutoMCU fraction images resulted in a 508 km^2 net reduction in forest from 1985 to 2009 (Figure 21.3). Comparatively, the MaFoMP maps generated a 566 km^2 reduction in forest from 1984 to 2009, demonstrating that CLASlite was within a 10% range of similar transitions over a similar time period. The CLASlite-generated forest cover–type maps resulted in an 81% kappa agreement with the MaFoMP maps and an average 85% accuracy when validated with randomly sampled Google Earth imagery.

21.6.1.2 Deforestation and Disturbance Mapping

Between 1985 and 2013, the study area exhibited a net forest change of 2301 km^2, equating to 19.5% of the study area (Table 21.10). The largest total amount of forest change was

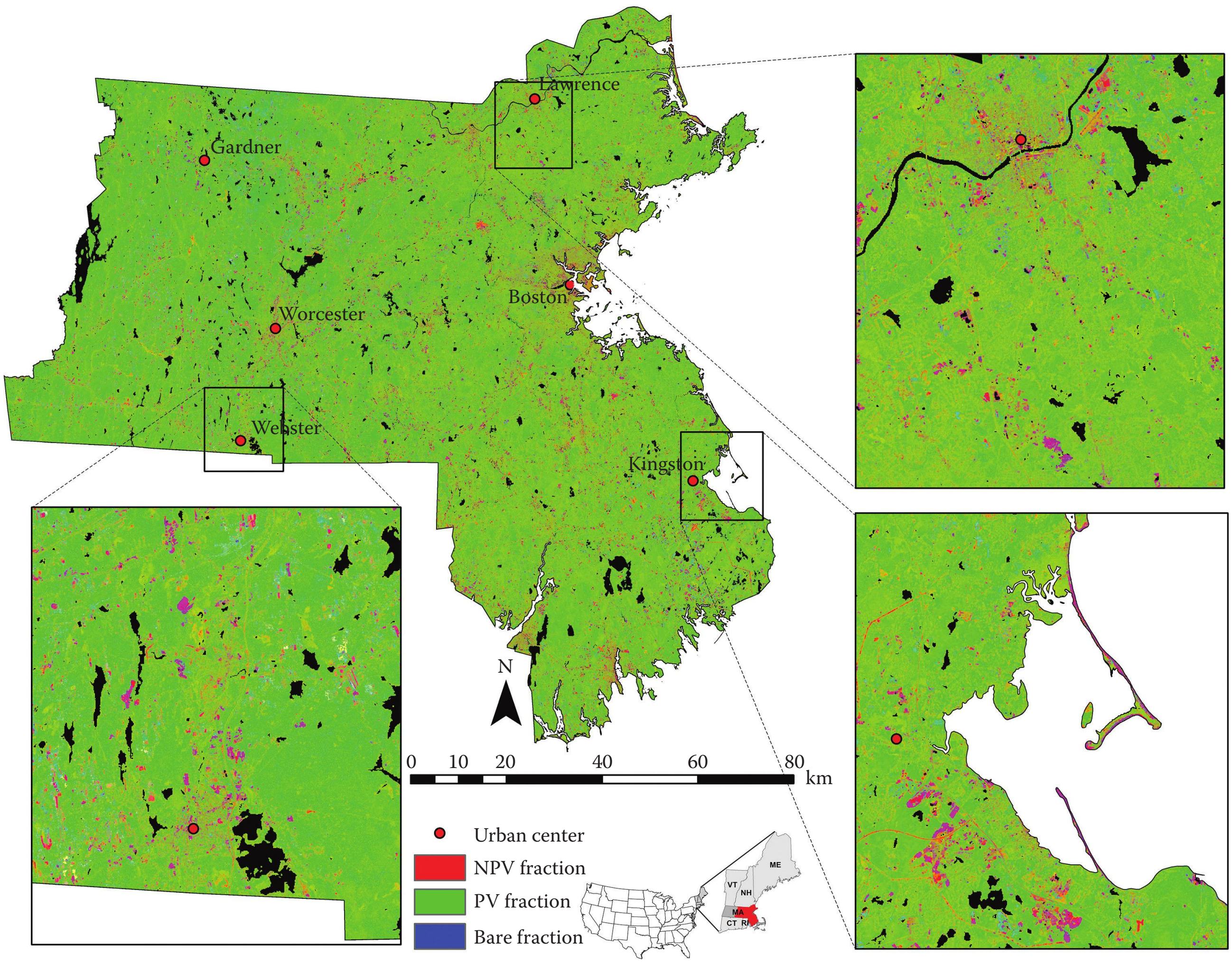

FIGURE 21.2 Study area in Central Massachusetts fraction composite image produced by CLASlite's AutoMCU with examples of rural (Webster), urban (Lawrence), and coastal (Kingston) landscapes.

observed between the interval of 1985–1993, followed by 1995–1999 and 2002–2009, respectively (Figure 21.5), representing 13.5% of the total area that was converted from forest to nonforest (Table 21.10). A visual assessment of the deforestation and disturbance results indicated that forest change was overestimated due to subtle variation in forest phenology, though CLASlite was able to detect most major land-clearing disturbances across one to many years.

21.6.1.3 Gardner, Massachusetts, Forest Change

The case study located in Gardner, Massachusetts (Figure 21.4), illustrated the rural to urban land conversion, a common trend throughout the study area. Forest cover was reduced by 15.2% from 1985 (105 km^2) to 2013 (84 km^2). Across all years, a systematic and continuous shift from forest to nonforest cover types is revealed (Figure 21.4). CLASlite forest cover maps for 1985 report 105 km^2, compared to the MaFoMP maps of 106 km^2. Concomitantly, the 2009 CLASlite output reported 87 km^2 of forested area remaining in Gardner, MA, compared to 96 km^2 in the MaFoMP product. The area differences between the 2009 classifications were less than 4% of the total case study area of Gardner, Massachusetts. Similar to the eastern Massachusetts deforestation and disturbance mapping, the amount of area affected by forest change in Gardner was overestimated. The total forest change from 1985 to 2013 was reported as being 33 km^2 (23%), where the greatest era of change was 1985–1993, followed by 1995–1999 and 2002–2009.

21.6.1.4 2011 Tornado Disturbance

On June 1, 2011, a 37 km long and 0.8 km wide tornado track touchdowned across southcentral Massachusetts (Figure 21.6). Using the 2010–2011 CLASlite deforestation output, we produced a detailed rendition of the tornado disturbed areas, encompassing 20.3 km^2 over the 60 km track (Figure 21.6). Two years posttornado disturbance, the 2013 forest cover image reported 4.8 km^2 of forest succession along the disturbance

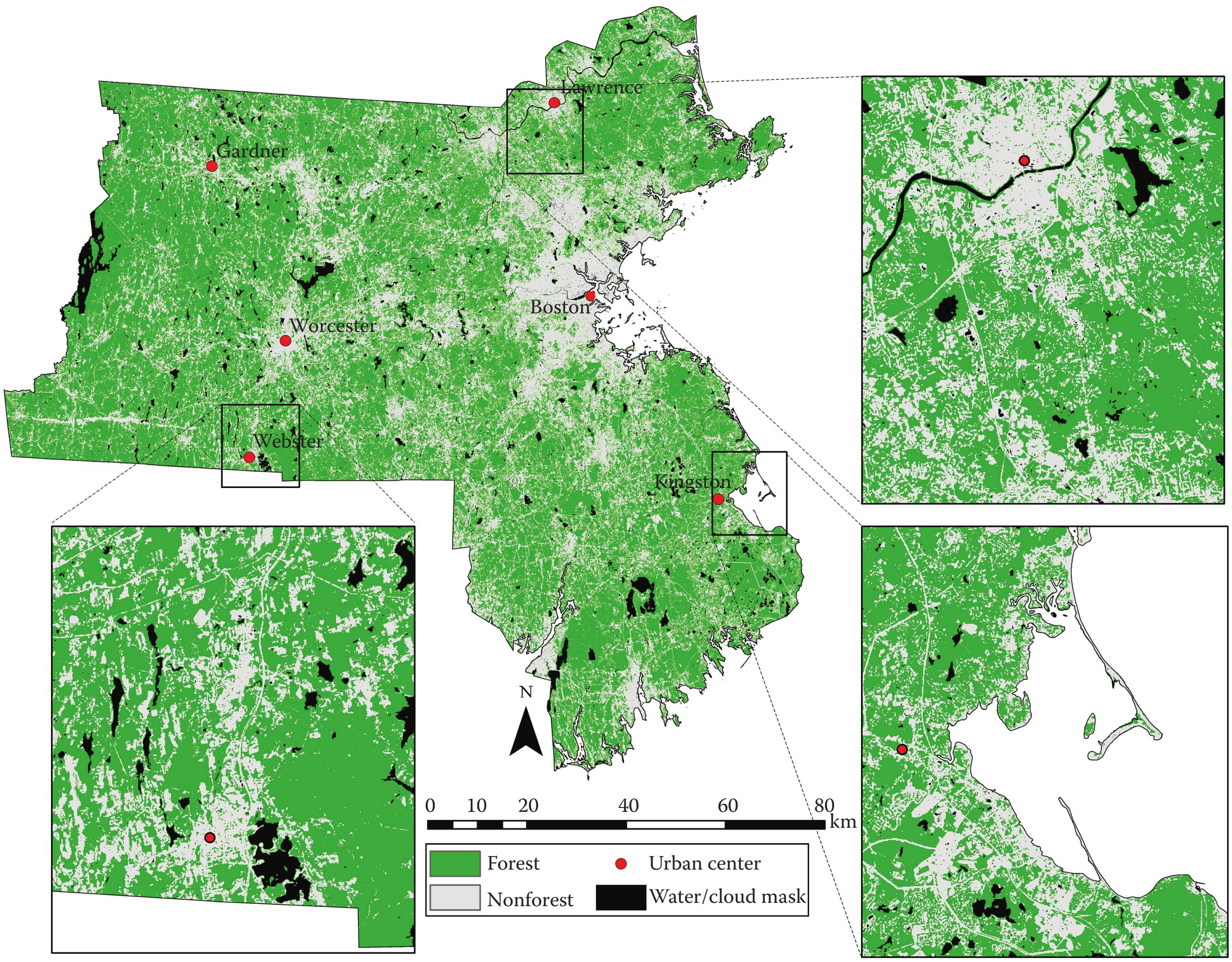

FIGURE 21.3 Statewide automated forest cover image for 2013, with examples of rural (Webster), urban (Lawrence), and coastal (Kingston) landscapes. CLASlite produced cloud/water mask is delineated in black.

edges, while 15.2 km^2 was still in a disturbed state. Based on 50 randomly sampled points, the agreement was 93% across the tornado track.

21.7 Knowledge Gaps and Future Directions

A remote sensing renaissance has begun. Not since the launch of Earth Resources Technology Satellite 1 in 1972 has the remote sensing community witnessed a more empowering era. Since the mid-1990s, most of the information bottlenecks to operational-style remote sensing research and application have begun to be opened wide for effective and sustainable Earth observation science. The MODIS and Landsat science teams have tenaciously pushed for free, accurate data, and information products, that can be accessed by the rapidly growing global user community. At the same time, high spatial resolution data are available globally from a variety of private companies, most notably (for view only) the Google Earth corporation, at 1–4 m. Importantly, the fields of Landscape Ecology and Land Change Science have claimed remotely sensed data as an invaluable component of their respective scientific practice. International charters such as the UN-SPIDER initiative rely completely on Earth observation data to draw attention to natural and humanitarian crises. As the content of this chapter highlights, the increased availability of coarse, medium, and high spatial resolution data and the surge in efficient automated methods place remote sensing science in a better place than it has ever been in 40 years. In the next 10 years, remote sensing practitioners can expect to see a multiplier effect with regard to remote sensing applications, as data, methods, and continued advocacy accumulate and expand to new fields and new problems. The following list highlights the current knowledge gaps and future directions for the remote sensing land change community:

1. Ironically, as more and more data become available, more data are needed. Referring to the Landsat program, there will be increasing demand for Landsat MSS data and also TM data that have not yet been catalogued. The collection and processing of these data from various agencies

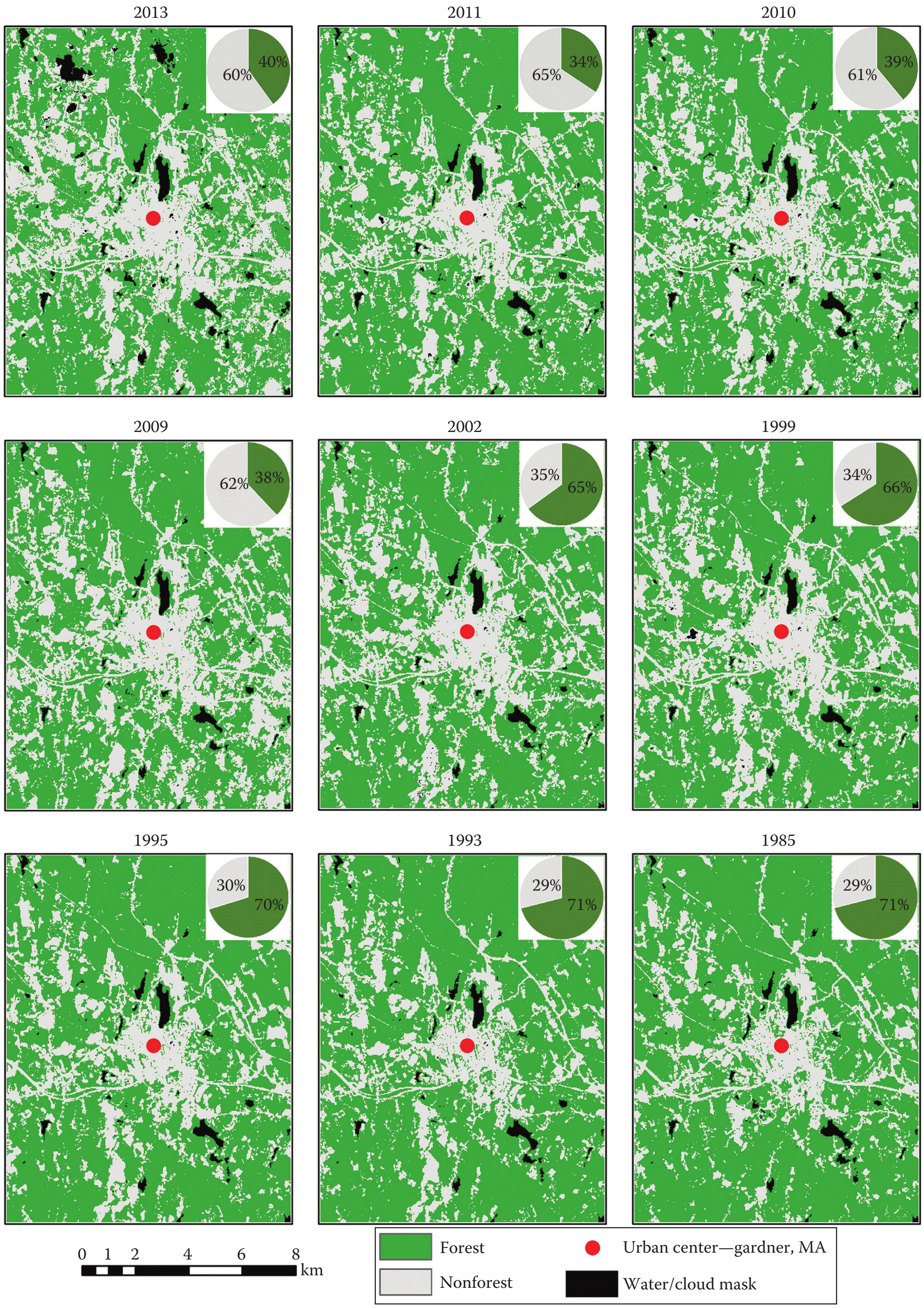

FIGURE 21.4 Forest cover temporal change sequence of Gardner, MA, from 1985 to 2013. Note, each forest cover scene has the percent proportion of pixels for forest and nonforest land cover classes.

TABLE 21.7 Cross Tabulation Assessment Showing Pixel Agreement for Like Years in Terms of Percent of Total Pixel

			MAFOMP							
			1984		1990		2000		2009	
	Year	Class	Forest	Nonforest	Forest	Nonforest	Forest	Nonforest	Forest	Nonforest
CLASlite	1985	Forest	0.545	0.078	—	—	—	—	—	—
		Nonforest	0.121	0.256	—	—	—	—	—	—
	1993	Forest	—	—	0.520	0.090	—	—	—	—
		Nonforest	—	—	0.085	0.305	—	—	—	—
	2002	Forest	—	—	—	—	0.510	0.118	—	—
		Nonforest	—	—	—	—	0.072	0.299	—	—
	2009	Forest	—	—	—	—	—	—	0.497	0.078
		Nonforest	—	—	—	—	—	—	0.128	0.297

TABLE 21.8 Kappa (a) and Cramer's V (b) Statistics Showing the Relative Pixel Agreement Accuracy of the CLASlite Forest Cover Classification to MaFoMP Imagery across Four Time Steps

		Kappa			
		MAFOMP			
	Year	1984	1990	2000	2009
CLASlite	1985	0.8183	—	—	—
	1993	—	0.8275	—	—
	2002	—	—	0.8179	—
	2009	—	—	—	0.81637
		Cramer's V			
		MAFOMP			
	Year	1984	1990	2000	2009
CLASlite	1985	0.7839	—	—	—
	1993	—	0.7864	—	—
	2002	—	—	0.7966	—
	2009	—	—	—	0.781

TABLE 21.9 Random Sample Pixel Percent Agreement of Forest Cover Types of the CLASlite Classification Against High-Resolution Google Earth Imagery

			Google Earth™									
			1995		2003		2008		2010		2013	
	Year	Class	Forest	Nonforest	Forest	Nonforest	Forest	Nonforest	Forest	Nonforest	Forest	Nonforest
CLASLite	1995	Forest	0.638	0.064	—	—	—	—	—	—	—	—
		Nonforest	0.037	0.25	—	—	—	—	—	—	—	—
	2002	Forest	—	—	0.613	0.032	—	—	—	—	—	—
		Nonforest	—	—	0.048	0.296	—	—	—	—	—	—
	2009	Forest	—	—	—	—	0.608	0.322	—	—	—	—
		Nonforest	—	—	—	—	0.032	0.317	—	—	—	—
	2010	Forest	—	—	—	—	—	—	0.585	0.032	—	—
		Nonforest	—	—	—	—	—	—	0.037	0.335	—	—
	2013	Forest	—	—	—	—	—	—	—	—	0.5945	0.0594
		Nonforest	—	—	—	—	—	—	—	—	0.0324	0.308

Note: With increasing time there is a direct relationship to decreasing forest and increasing nonforest agreement.

TABLE 21.10 Change Statistics per Era

Era	Deforestation Total	Deforestation (%)	Disturbance Total	Disturbance (%)	Forest Change Total
1985–1993	565.37	4.81	318.21	2.71	883.58
1993–1995	57.1	0.49	29.42	0.25	86.52
1995–1999	250.76	2.13	168.48	1.43	419.24
1999–2002	105.49	0.90	40.57	0.35	146.05
2002–2009	215.35	1.83	119.56	1.02	334.91
2009–2010	81.14	0.69	65.39	0.56	146.54
2010–2011	82.88	0.71	82.52	0.70	165.4
2011–2013	44.97	0.38	74.01	0.63	118.97
Total	1403.06	11.94	898.15	7.65	2301.21

Forest change is the sum of disturbance and deforestation.

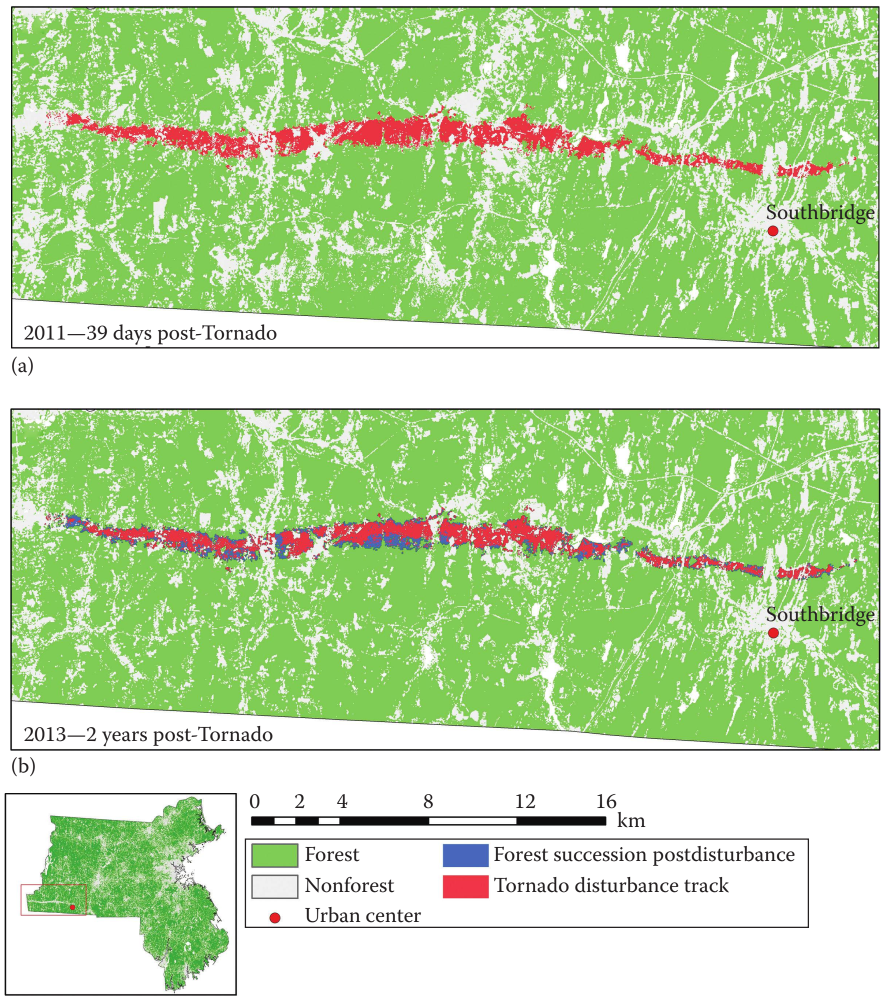

FIGURE 21.5 Deforested tornado track as depicted by the CLASlite 2010–2011 deforestation class output (a). Two years post disturbance (b), note that successional infill (blue) has dominated the outer edges of the tornado track, while the interior of the tornado track (red) is still in a deforested state.

throughout the world will greatly extend the reach of the Landsat program, especially to developing countries—the very locations where land change scientists focus their research. Additionally, the cost of high spatial resolution data is problematic. One to four meter data are indispensible for locations where in situ data are unavailable, but these data can currently only be purchased by governments or government-affiliated research initiatives.

2. Given the importance placed currently on land cover modifications by the land change science community, it is important to distinguish their occurrence from land cover conversions. This is a difficult task because both types of

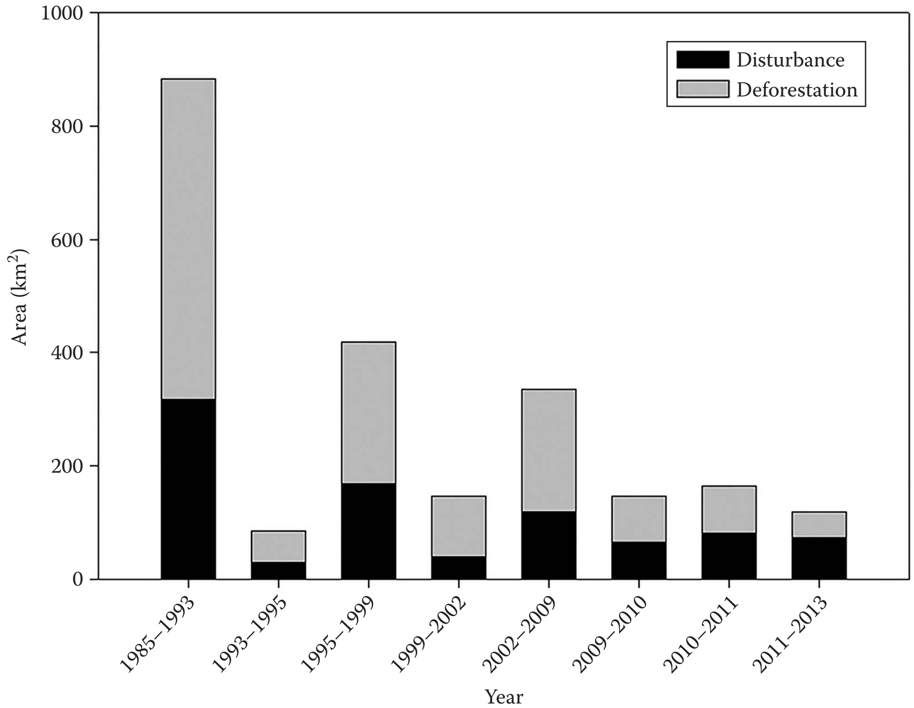

FIGURE 21.6 Area deforested in km^2 per time step across eastern Massachusetts.

change can result in similar magnitudes of reflectance in a change detection scenario. New methods are needed to ameliorate this problem, especially in developing countries where operational data availability can be scarce.

3. The remote sensing change detection community has laid a strong framework on the back of optical remote sensing imagery. While this paradigm is highly rewarding, optical data are limited in a variety of situations, especially concerning mapping in cloud-prone and data-poor locations. The next decade should hopefully see an expansion in the availability use of large-area radar and LIDAR data collections such that landscape monitoring will be as complete in Cameroon as it is in the United States.
4. All land cover change detection and monitoring relies on the availability of accurate land cover/use information for every location where remotely sensed data are captured. Unfortunately, the process of conducting change detection for a given location is hampered by the paucity of reliable ground reference, wildlife habitat, agricultural land use, and ecological disturbance information. In the next decade, it is hoped that this knowledge gap will be at least partially filled through continued land cover/use mapping efforts, as well as map data sharing.

Acknowledgments

The authors thank David Wilkie and Robert Rose (Wildlife Conservation Society) who inspired the ideas that laid the basis for this chapter. Thanks are also extended to Luisa Young (Clark University), Doug Stow (San Diego State University), and Janet Franklin (Arizona State University) for their contributions to this work.

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