6 Integrating GIS and Remotely Sensed Data for Mapping Forest Disturbance and Change

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CONTENTS

INTRODUCTION

Scientists and policy makers from various institutions and agencies are currently devoting substantial time and resources to study of the implications of environmental change in forests and woodlands, the most widely distributed ecosystem on the earth (McIver and Wheaton, 2005; Wulder, 1998). In the context of environmental remote sensing, forest change, manifested as forest attribute modification or conversion, can occur at every temporal and spatial scale, and changes at local scales can have cumulative impacts at broader scales (Loveland et al., 2002). Natural resource managers and environmental modelers thus require reliable information about the ecological impacts associated with natural and anthropogenic disturbances to forests (Bricker and Ruggiero, 1998; Mladenoff, 2005).

Current understanding of the extent and rate of forest change is inadequate because (a) long-term large-area monitoring, suited to mapping conversions and transitions, is in its operational infancy (S. E. Franklin and Wulder, 2002); and (b) modifications to forest condition/abundance are difficult to detect with reliable precision (Gong and Xu, 2003). As such, researchers and policy makers "lack … quantitative, spatially-explicit and statistically representative data on land-cover change" (Lambin, 1999, p. 191). To redress this deficiency, the GIS science community has begun to explore new ways to detect, characterize, and monitor forest change through the integration of remote sensing and GIS (geographical information system) data and technologies (Kasischke et al., 2004).

Such changes correct throughout? Or do you mean to indicate specific organizations, groups?

The integration of remotely sensed and GIS data* takes four forms: (a) GISs can be used to store multiple data types; (b) GIS analysis and processing methods can be used for raster data manipulation and analysis (e.g., buffer/distance operations); (c) remotely sensed data can be manipulated to derive GIS data; and (d) GIS data can be used to guide image analysis to extract more complete and accurate information from spectral data. This chapter focuses on the fourth topic, with acknowledgment of the gains made by the academic GIS science community in the areas of spatial analysis, landscape conceptualization, and map validation (National Center for Geographic Information and Analysis [NCGIA], 2005).

GIS data, such as topographic variables, were first integrated in remote sensing-based vegetation mapping studies in the late 1970s because available satellite data (e.g., Landsat MSS) did not provide sufficient floristic detail for effective resource management (see Franklin, 1995, and references therein). For many applications, this problem is still current. The rationale for incorporating topographic variables in single-date forest mapping is based on their correlation with forest species or lifeform composition (Guisan and Zimmerman, 2000). For example, the Utah GAP

Define MSS.

Define GAP.

* *GIS data* in this chapter refers to all nonspectral digital entities included and used in forest mapping/monitoring applications. GIS data have also been described as "collateral" and "ancillary" as compared to "primary" remotely sensed data (Jensen 2005).

land cover mapping program uses topographic data (elevation, slope, aspect, and position index) and soil data (carbon content, available water, and quality) to produce fine-scale vegetation maps (C. Huang et al., 2003). In spite of the substantial improvement in remote sensing technology and data quality (spatial and spectral resolution) since the 1970s, however, the need for contextual GIS data has actually increased because remote sensing scientists are posing more complex questions than ever before (e.g., land change science; Turner et al. 1999; Turner, 2002). Including GIS data with remotely sensed data for the discrimination of land cover classes typically results in higher overall map accuracies (e.g., increases of 5–10% overall) over those produced using spectral-radiometric data alone (Frank, 1988; Senoo et al., 1990; Strahler et al., 1978; Talbot and Markon, 1986; Trietz and Howarth, 2000). For a review of recent advances in land cover mapping, see the work of S. E. Franklin and Wulder (2002) and J. Franklin et al. (2003).

Forest change mapping and monitoring is feasible when changes in the forest attributes of interest result in *detectable* changes in image radiance, emittance, or microwave backscatter values (Coppin et al., 2004). Forest disturbances vary by type, duration, and intensity (Gong and Xu, 2003). Disturbances such as wildfire, insect infestation, disease, timber harvest, ice storms, flooding, and strong winds usually result in highly variable (spectrally and spatially) damage at scales ranging from leaves to landscapes (Attiwill, 1994). Accurate remote sensing assessment of disturbance impact, severity, and rate of recovery (succession) can therefore be difficult and even impossible in substantially heterogeneous landscapes in relation to the sensor's spatial, spectroradiometric, and temporal characteristics (Rogan and Chen, 2004). When *known* or *perceived* changes to forest attributes occur but cannot be detected, located, or characterized to an acceptable confidence level, GIS data can thus play an important role in facilitating more robust change mapping (Rogan et al., 2003).

Change detection analysis employing both GIS coverages and remotely sensed data obtained prior to and following a disturbance has been used to assess specific types of forest and woodland damage, including vegetation cover responses to drought (Jacobberger-Jellison, 1994; Peters et al., 1993); insect outbreaks (S. E. Franklin et al., 2003; Nelson, 1983); windthrow (Cablk et al., 1994; Johnson, 1994); ice storm impacts (Olthof et al., 2004); and timber harvest (Nepstad et al., 1999' Sader et al., 2003). In many of these studies, the integration of spectral and GIS data was shown to improve substantially impact/damage assessment and map accuracy.

The objectives of this chapter are to describe how GIS data and technology can be utilized as a tool to characterize forest disturbance and change, how GIS data can be used to complement remotely sensed data, and how they can be used together to map and model forest conversions and modifications.

INTEGRATION OF GIS AND REMOTELY SENSED DATA

Complete integration of remotely sensed and GIS data is a long-standing problem that has drawn the attention of the International Society of Photogrammetry and Remote Sensing (Commission IV) and the (U.S.) NCGIA (Initiative 12). The inte-

gration of GIS data with remotely sensed imagery has witnessed increased interest for the following reasons:

1. Increased data availability, quality, and decreased data costs across large study extents (Davis et al., 1991; Emch et al., 2005; Treitz and Rogan, 2004)
2. Development of large-area forest mapping/monitoring projects using a wide variety of spectral data captured by different platforms, featuring disparate spatial and spectroradiometric characteristic capabilities (e.g., MSS vs. Advanced Spaceborne Thermal Emission and Reflection Radiometer) (Franklin and Wulder, 2002)
3. Demand for more precise estimates of disturbance impacts with Landsat-like data (i.e., spatial and thematic resolutions) (Seto et al., 2002; Varjo, 1997; E. H. Wilson and Sader, 2002)
4. Growing need for automated mapping and map updating in complex landscapes using expert systems/knowledge-based classification (X. Huang and Jensen, 1997; Lees and Ritman, 1991; Raclot et al., 2005)
5. Demonstrated potential of data integration/fusion for predictive forest change mapping (Baker, 1989; Mladenoff, 2005; Rogan et al., 2003)

Gahegan and Flack (1999) stated that the relationship between remote sensing and GIS practitioning has traditionally been that of supplier (remote sensing) and consumer (GIS). Typical remote sensing-derived products used in GIS analyses include baseline forest cover and lifeform maps (S. E. Franklin, 2001) and forest cover change maps used for map updating (Levien et al., 1999; Zhan et al., 2002); these are available at spatial resolutions typically ranging from 10 m to 1 km. The current spatial and spectral capabilities and limits of baseline mapping for generic change detection are discussed in detail in the work of J. Franklin et al. (2003) and Rogan and Chen (2004). In addition, digital elevation models (DEMs) can be generated using a variety of sensors and established methodologies (S. E. Franklin, 2001). The primary methods for DEM production are stereogrammetric techniques using air photos (photogrammetry), optical spaceborne imagery (SPOT [Systeme Pour d'Observation de la Terre] and Advanced Spaceborne Thermal Emission and Reflection Radiometer), and radar data (interferometry). Airborne light detection and ranging (LIDAR) data have been applied to terrain mapping. While LIDAR-derived DEMs have fine spatial resolution and high horizontal and vertical accuracy, currently they do not offer widespread coverage (Jensen, 2005; Lim et al., 2003), with some regional exceptions such as the Puget Sound Lidar Consortium (http://rocky2.ess.washington.edu/data/raster/lidar/index.htm). In addition, the extraction of linear features such as roads, trails, and streams using high spatial resolution optical data has reached a high level of sophistication and automation (Song and Civco, 2004).

Remote sensing analysts have become avid consumers of GIS data as a means to add value to remotely sensed data and analysis (S. E. Franklin, 2001). While there are many superficial similarities between GIS and remotely sensed data, a few conceptual differences make the complete integration of GIS and remote sensing challenging. Dobson (1993) noted two chief problems related to remote sensing and

GIS integration, such as incompatible data types (e.g., DEMs and census data) and the lack of an integrated approach to spatial data handling. Lees (1996) noted that the separate operational data spaces of spectral and spatial (GIS) variables must be acknowledged to conduct meaningful analysis. GIS data space is defined by the values of the direct/indirect variable of interest (e.g., elevation, temperature), while spectral data space consists of a discrete slice of the electromagnetic spectrum, which the remote sensing community needs to address further (Lees, 1996). Gahegan and Ehlers (2000) discussed the transformation process from a remotely sensed image to classified theme to subsequent GIS object and the error propagated at each step. Gahegan and Flack (1999) added that benefits to more seamless integration include the potential for more specific, and therefore more meaningful, data products and the ability to use GIS products to provide typicality information (e.g., ecological structure and function) as well as ancillary data to add more information to remotely sensed products (see also Aspinall, 2002).

GIS data are integrated in forest cover mapping and monitoring in three primary ways (Hutchinson, 1982):

1. Preclassification stratification — partitioning the study area based on elevation gradients or watershed boundaries to minimize the number of spectral classes or separate classes that are spectrally similar but geographically distinct (Cibula and Nyquist, 1987; J. Franklin et al., 1986; Vogelmann et al., 1998). This method is particularly relevant in forest disturbance contexts to mask either irrelevant or confounding scene features (Coppin et al., 2004).
2. Postclassification sorting — partitioning mapped categories based on soil type or slope to disaggregate or refine class membership* (Loveland et al., 2002; Satterwhite et al., 1984; Shasby and Carneggie, 1986). This method is in wide application in expert knowledge base approaches (X. Huang and Jensen, 1997).
3. Direct inclusion — combining ancillary variables with spectral data in a classification† (Ricchetti, 2000; Rogan et al., 2003; Wulder et al., 2004). This method is in increasing use with machine learning classification algorithms.

The first two methods are analytical and assume that the analyst has "expert" knowledge of the study area and can therefore use environmental relationships in the ancillary data (e.g., slope) to stratify the remotely sensed data so they will be manipulated differently (e.g., one slope interval vs. another) via preclassification stratification. Postclassification stratification uses expert knowledge to aggregate map classes based on environmental relationships (e.g., vegetation classes can be stratified by elevation zones). Typically, the use of either continuous or discrete

* This may be applied to refine categories generated using supervised classification or to label unsupervised classes.

† Strahler (1980) also suggested the use of ancillary variables to calculate prior probabilities for the maximum likelihood classifier to improve map accuracy, and this has been implemented in large-area mapping using decision trees (McIver and Friedl 2002).

ancillary data is dependent on the classification technique used (Brown et al., 1993), with similar variables represented as discrete (i.e., separated categories at critical thresholds) or continuous (i.e., distance-based or interpolated coverage maps and surfaces) in accordance with the input requirements. The first two methods have therefore been used previously when parametric classification algorithms are employed because they are unable to handle categorical inputs directly (Strahler, 1980). Direct inclusion takes an empirical approach to mapping where the ancillary variables are included in the classification process with remotely sensed data potentially to provide additional information for improved class discrimination (Rogan et al., 2003). Wulder et al. (2004) stressed the need for data rescaling when DEM data are included with remotely sensed data involving parametric classification algorithms. Both continuous and discrete data are handled readily by nonparametric machine learning algorithms (MLAs), however (Rogan et al., 2003; Saveliex and Dobrinin, 2002).

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GIS Data as Environmental Variables

The selection of input data for forest disturbance mapping and monitoring can have a significant impact on the final map product (Gong and Xu, 2003). Even when using relatively simple processing algorithms such as a minimum distance classifier, GIS data can facilitate detection and discrimination of target features, which could prove more beneficial than scarce or poor-quality input data processed with a complex algorithm. Biological, physical, and socioeconomic properties of the environment strongly influence land surface processes and human behavior and subsequently vegetation composition, abundance, and condition (Steyaert, 1996; Warner et al., 1994). This makes the selection and characterization of these variables increasingly important (Guisan and Zimmerman, 2002). Further, Skidmore (1989) noted that the relative importance of different types of GIS data can vary by spatial scale. For example, topographic data can improve land cover map accuracy at local to regional scales, whereas climate data become more important at regional to global scales.

GIS data that are potentially important in mapping, monitoring, and modeling forest change are described in Table 6.1. Variables that describe topography have been used in most environmental modeling applications (J. Franklin, 1995; Guisan and Zimmerman, 2000) as they are correlated with vegetation distribution at a finer spatial scale than climate variables (J. P. Wilson and Gallant, 1998; see Florinsky, 1998, for review of relationships between topographic variables and landscape characteristics). Simple topographic variables such as elevation, slope, and aspect most often represent indirect gradients (*sensu* Austin and Smith, 1989) with respect to forest species distribution. Slope, however, can be considered a direct variable in the context of disturbance such as fire (i.e., slope steepness is directly related to flame length and burn intensity) (Rogan and Yool, 2001).

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Figure 6.1 presents a conceptual diagram of a forest disturbance mapping/modeling scenario. The impact of abiotic and biotic disturbances on a forest stand is mostly determined by the interaction of the intensity of dynamic disturbances (e.g., wind speed) and their severity, or immediate impact, as mitigated/enhanced by static factors (i.e., topography), and the intrinsic properties of the forest stand (i.e., com-

TABLE 6.1
Potential GIS Data in Forest Change Studies

Variable type/source	Examples	Typical resolution	Type	Source	Association
Topography: http://seamless.usgs.gov/website/seamless/		1:24,000 (~30 m)			
	Simple: elevation, slope, aspect		Continuous, ordinal	DEM	Climate, soil characteristics, disturbance-behavior
	Complex: topographic moisture index, incoming solar radiation, landscape position		Continuous, ordinal, categorical	Formulae using DEMs	Soil texture, available moisture, temperature
Climate: http://www.wcc.nrcs.usda.gov/climate/prism.html		~4 km	Continuous	Interpolated weather station data	Available moisture
	Minimum January temperature, maximum July temperature, summer precipitation				
Disturbance: http://glcf.umiacs.umd.edu/data/modis/vcc/index.shtml		~1 Ha (MMU)	Categorical, ordinal	Compiled, field work, aerial sketch/survey	Disturbance process (type and intensity/severity)
	Wildfire burn scar perimeters				
	Insect pest infestation perimeters				
	Ice storm damage intensity perimeters				
	Timber harvest removal/type perimeters				
Forest inventory: http://fia.fs.fed.us/		Variable	Categorical, ordinal	Compiled, field works	Species/stand abundance, condition, composition
	Stand age, species, dbh, density, height, crown bulk density				
Socioeconomic: http://www.census.gov/geo/www/index.html		1:100,000	Categorical	U.S. Census	Anthropogenic influence/policy

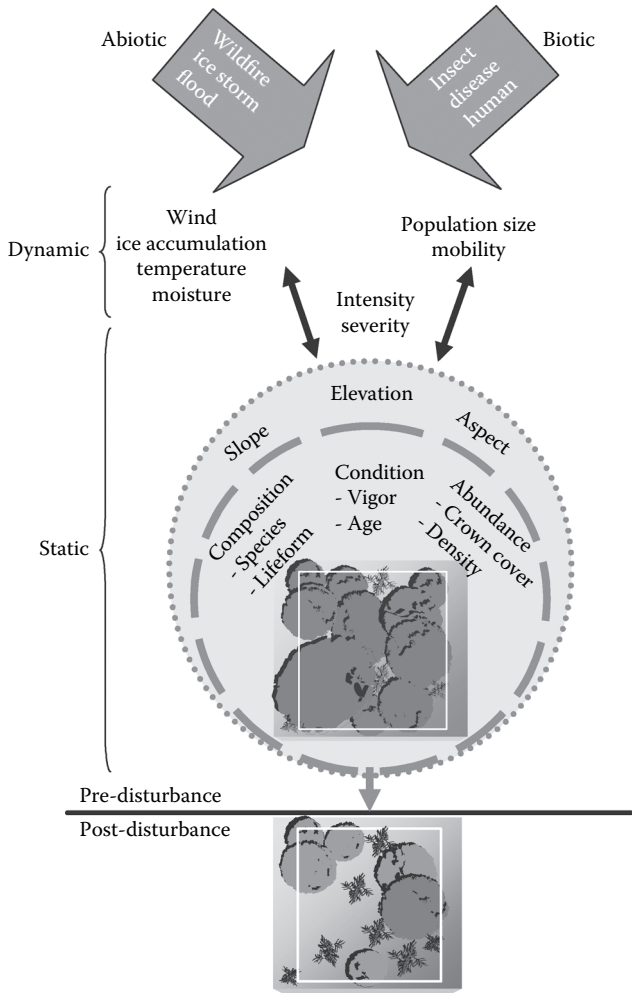

FIGURE 6.1 Forest disturbance mapping/modeling paradigm.

position, condition and, abundance). Because frequent and accurate data representing dynamic drivers of disturbance are rare and costly to collect, readily available static variables (e.g., elevation and slope) are more often used in conjunction with remotely sensed data to map both disturbance and disturbance-risk (Medler and Yool, 1997). For example, Khorram et al. (1990) found the indicator of conifer forest decline, as defined by the percentage of defoliation, to be a function of Landsat-5 Thematic Mapper (TM) (near infrared), elevation, and aspect.

Complex topographic variables (e.g., topographic moisture index, incoming solar radiation) can have more direct influence on forest distribution and usually describe a combination of factors such as soil texture and water availability associated with the microclimate of a location (see Moore et al., 1991). The U.S. Geological Survey provides a standard 1:24,000 (7.5-min) digital DEM data set for the conterminous

United States (10-m DEM coverages are also available for some areas; see http://edc.usgs.gov/products/elevation/ned.html). In 2000, the Shuttle Radar Topography Mission obtained elevation data on a near-global scale to generate the most complete high-resolution digital topographic database of Earth. The University of Maryland Global Land Cover Facility editions of Shuttle Radar Topography Mission data are available in three general formats: 1 arc-sec (30 m) of the United States; 3 arc-sec (90 m) of the world; and 30 arc-sec (1 km) of the world (http://www.landcover.org) (see Table 6.1).

Climate has a direct influence on forest distribution, typically through extremes in temperature and precipitation amounts. Some of the earliest fine spatial resolution (4-km) climate maps were produced through collaboration between Natural Resources Conservation Service National Water and Climate Center and Spatial Climate Analysis Service at Oregon State University. Based on a model named PRISM (parameter-elevation regressions on independent slopes model), factors such as rain shadows, temperature inversions, and coastal effects were incorporated in the climate-mapping process (see http://www.ocs.orst.edu/prism/). Liu et al. (2003) included elevation and temperature variables to map the entire land cover of China.

Existing land cover and land use data can be crucial for land cover stratification and vegetation sampling and analysis. The historical legacy of a particular land use on vegetation distribution has been examined (Foster et al., 1998). For example, Pan et al. (2001) reported that physical attributes explain only a small portion of the abundance of conifer species located on past abandoned land compared to land use factors. The U.S. Geological Survey provides a land use and land cover data set with 21 possible cover type categories, based primarily on manual interpretation of 1970s and 1980s aerial photography (see http://edc.usgs.gov/products/landcover/lulc.html). Existing vegetation maps, however, are currently considered too coarse for detailed analyses (Coulter et al., 2000, p. 1329). Soil type provides information on texture, moisture and nutrient availability, and pH and has been used to prestratify a boreal forest based on mineral soil type to reduce the influence of soil background variation of timber harvest mapping (Heikkonen, 2004). Soil data, both spatial and tabular, are available from the (U.S.) Natural Resources Conservation Service.

Contextual socioeconomic data such as roads, distance to roads, and human population (census) have been directly linked to forest change, usually in the form of proximity to disturbance "potential" (Eastman et al., 2005). Chen (2002) discussed the limitations involved in selecting an appropriate scale to which census data should be disaggregated to be compatible with raster-based imagery (and GIS data). Mertens et al. (2001) combined ecological, economic, and remotely sensed data to predict the impact of logging activities on forest cover in east Cameroon. Results showed that the occurrence of logging-induced forest cover modifications increased with the value of forest rent.

Disturbance-related GIS data include burn scar perimeters, timber harvest polygons, and flood maps and have been used in a variety of ways, including

1. Masking previous/other disturbances not of interest to the mapping exercise
2. Calibrating and validating classification algorithms

3. Testing the effectiveness of spectral change-thresholding procedures
4. Validating forest disturbance products derived from remotely sensed data

While extremely useful for change mapping studies, supporting GIS data are rarely collected in a repeated and consistent manner or the same spatial resolution. For example, in California, burn scar perimeters are available at 4-Ha minimum mapping unit (MMU) on U.S. Forest Service lands, while state forest lands provide 121-Ha MMU data. However, 500-m 16-day moderate resolution imaging spectrometer (MODIS) burn scar products have recently become available for large-area fire monitoring (see http://edcdaac.usgs.gov/modis/dataproducts.asp). Daily maps of active thermal hot spots are available from the MODIS 8-day 1-km active fire summary product data, indicating the spatial location of active fires (Roy et al., 1999).

Errors in GIS Data

No digital data set is error free. An essential condition for successful integration of GIS and remotely sensed data is an understanding of the error contained in the data and propagated in subsequent analyses (Hinton, 1999). The topic of uncertainty (i.e., a quantitative statement about the probability of spatial data error) is a central theme in GIS science literature. Accuracy assessment of land cover from remotely sensed data is a mature topic (Foody, 2002). In contrast, accuracy assessment of the results of change detection applications have received a relatively modest amount of attention in the remote sensing (change detection) literature (Woodcock, 2002). Categorical variables such as soil type or land use are prone to errors, such as positional, topological, and attribute inaccuracies. Guisan and Zimmerman (2000) noted the importance of high accuracy in categorical variables because they often act as "filters" for primary prediction when combined with continuous variables such as elevation. While categorical data may be perceived to be more "accurate" than remotely sensed representations when presented in vector format (e.g., crisp boundaries), they can often have a coarser minimum mapping unit than the image data (Coulter et al., 2000).

Continuous variables, specifically topographic variables, have special importance in forest change mapping because they are commonly used in the derivation of additional variables (see Hunter and Goodchild, 1997). The accuracy of topographic variables depends primarily on the accuracy of the DEM from which they were derived (Florinsky, 1998). Various studies have investigated the effect of error in DEMs on data derived from them (Bolstad and Stowe, 1994; Hunter and Goodchild, 1997; Lees, 1996). For example, slope computed from a DEM not only is affected by the algorithm used to derive it, but also is affected by the precision of the elevation values in the DEM (Perlitsch, 1995).

It has generally been accepted that, as the steps involved in derivation of a topographic variable increase, so does its susceptibility to error (Guisan and Zimmerman, 2000). Van Niel et al. (2004) noted that this is not always the case, however. In a study that simulated the propagation of error in topographic variables, they found that in some cases more complex variables such as net solar radiation were less affected by error than relatively simple variables such as slope and aspect (Van

Niel et al., 2004). Holmes et al. (2000) similarly found that topographic variables derived by compounding values from a large number of DEM grid cells were affected by errors most dramatically, and that while global error estimates may be low, their local measurements could be quite high.

In summary, the key challenges associated with a more complete understanding of error in GIS variables involves a lack of procedures or protocol for quality control of integrated data (geometric accuracy and thematic detail) and issues related to different levels of data abstraction and representation (resolution and scale). Finally, a common, yet often unreported, issue is that dynamic GIS data representations such as land cover/use are out of date as soon as they are produced and may cause map errors when used for image masking, class sorting, or predictive modeling (Steyaert, 1996).

CONTRIBUTION OF GIS DATA TO FOREST CHANGE MAPPING

The typical forest change detection and mapping process consists of the following steps: (a) acquisition and coregistration of multidate imagery; (b) radiometric processing; (c) image transformation and change mapping; and (d) validation and change analysis (Coops et al., Chapter 2, this volume). GIS data are important for all four steps (Table 6.2).

EDITOR: Cross reference to Chapter 2.

Data Acquisition and Coregistration

Data Acquisition

From the outset of a change-mapping project, GIS data can be used to delineate specific "mapping zones" (Homer and Gallant, 2001), such as geographic areas (political boundaries), biomes (ecoregions), topography (watersheds), and land cover/use/ownership. The use of mapping zones can serve to maximize spectral uniformity, provide boundary delineation, and partition the workload into "logical, feasible units" (S. E. Franklin and Wulder, 2002, p. 16). Ramsey et al. (1995) concluded that ecoregions could be characterized based on phenological variation of vegetation cover using normalized difference vegetation index distribution maps as surrogates for net primary productivity. Bergen et al. (2005) used major land resource areas defined by biophysical and socioeconomic constraints.

In many forestry applications, the "stand" is used as the minimum unit of analysis rather than the pixel (J. Franklin et al., 2003) because medium-resolution Landsat TM pixels often possess higher spatial resolution than the vegetation attributes under investigation. Image segmentation has thus been applied to image data to delineate forest stands (J. Franklin et al., 2000). At fine spatial scales, which may have specific geographic features for detailed study, rivers and roads are often used for landscape delineation. For example, Congalton et al. (2002) used stream buffers to aid identification and monitoring in a riparian forest. GIS data can also be used to delimit target features or "damage zones" on thematic scales as broad as "the damaged area"

TABLE 6.2
Contribution of GIS Data to Forest Change Mapping

Task	Contribution of GIS	GIS data: Continuous	GIS data: Categorical
Data set selection	Biome delineation	Topography	Land/vegetation cover, land use, land ownership, political boundaries
	Study area boundary		
	Delimiting targeting features	n/a	Disturbance polygons
Image preprocessing	Geometric correction	DEM, GPS coordinates	Roads, streams
	Orthorectification	DEM	n/a
	Terrain correction	DEM	n/a
Image enhancement	Choice of transformation	DEM, slope	Vegetation, soils
Detection and mapping	Map legend(s)	n/a	Land cover/vegetation
	Stratification (masking); segmentation	DEM, slope, aspect	Soils, land/vegetation cover
	Change thresholding	n/a	Disturbance perimeters
	Calibration	Topography	Vegetation, soils, distance to roads[a]
	Choice of classification model (i.e., parametric vs. nonparametric)	All	All
	Validation	GPS coordinates	Vegetation, disturbance perimeters[a]
Change analysis	Cross tabulation/area summaries	Topographic variables	Land cover/use/ownership
Change modeling	Explanatory variables	All	All

[a] Extant.

Provide definition of "n/a" here.

to scales as fine as individual patches (e.g., wildfire burn scar and timber harvest plan perimeters) (e.g., Rogan and Yool, 2001; E. H. Wilson and Sader, 2002).

Geometric Correction

Image data acquired by satellite and airborne sensors are affected by systematic sensor, platform-induced, and terrain distortions that are introduced when image geometry is not perpendicular. Accurate per-pixel registration of multitemporal remotely sensed data is essential for forest change mapping because the potential exists for registration errors to be interpreted as forest cover change, which can lead to overestimation of actual change (Stow, 1999). Distortions in image data can be corrected by developing a model to tie per-pixel image features to GIS-based ground features (e.g., roads, streams, ridgelines [DEM], topographic maps). Further, in mountainous areas, terrain displacement can be hundreds of meters. For example, the 4-m multispectral image product from the IKONOS-2 will have nearly 600 m of terrain displacement if the sensor acquires data over an area with a kilometer of vertical relief where the sensor has an elevation angle of 60° (30° from nadir). To remove the terrain distortions accurately, DEMs are used to perform image orthorectification on optical and microwave data. Unfortunately, one of the shortcomings of current DEMs is that spatial resolution is often too coarse for orthocorrecting fine-resolution remotely sensed data such as QuickBird (2.5-m spatial resolution-multispectral) (Jensen, 2005).

Define IKONOS.

Radiometric Processing (Terrain Correction)

DEMs and vegetation maps are commonly used in topographic normalization (terrain correction) of optical and microwave data. For optical data, terrain correction procedures are typically based on a model that adjusts the radiance values measured by a sensor using data depicting the local terrain (Smith et al., 1980). The Minnaert model is used for topographic normalization, so called because reduction of topographic effects in each image pixel is based on the generation of a normalized radiance value (i.e., the radiance that the pixel would have if the terrain within the scene was flat). Because the Minnaert approach does not assume that surface cover is a perfect diffuse reflector, it requires the calculation of a photometric (Minnaert) constant K that is specific to land/vegetation cover; thus, implementation requires in-depth knowledge of the study area. Additional details on radiometric processing can be found in Chapter 2.

EDITOR: Cross reference to Chapter 2.

Image Transformation and Change Mapping

Classification Scheme/Map Legend

The choice of change detection approach (i.e., categorical comparison and continuous comparison) can profoundly affect the quantitative estimates of forest change (Rogan and Chen, 2004). A problem with many forest cover classification schemes is that the map categories are not always mutually exclusive, which results in class confusion (Gong and Xu, 2003). Class confusion is prevalent in unitemporal forest

disturbance mapping (Rogan and Franklin, 2001). For example, locally lower forest biomass caused by an ice storm could be confused with a recently harvested forest stand or senesced pastures with similar spectral properties. GIS data can be invaluable for minimizing class confusion. Bitemporal change detection does not suffer the shortcomings of single-date, postdisturbance methods, but subtle change detection can benefit from the integration of GIS data (Coppin et al., 2004). For example, Rogan et al. (2003) reported that environmental variables such as elevation and slope were selected using a classification tree algorithm when the forest change classification scheme involved nine discrete canopy cover change classes. This situation contrasted sharply with variable selection using a simple change versus no change classification scheme, in which only remotely sensed variables were selected by the classification tree algorithm. Table 6.3 presents examples of studies that have integrated remotely sensed and GIS data for forest change/disturbance mapping and monitoring. Simple topographic variables such as elevation and slope have been used most often in integrative remote sensing-GIS mapping studies.

Land cover and land use data are typically used to perform stratified random sampling for field data collection. Detailed forest inventory information about stand type, structure, and age has been used successfully to map insect damage through the stratification of the calibration data set. These data were used to reduce the variability in the calibration data based on logical decision rules related to host susceptibility and forest structure (see S. E. Franklin and Raske, 1994; S. E. Franklin et al., 2003; Skakun et al., 2003).

Classification Rule

McIver and Friedl (2002) emphasized that all land cover classifications contain elements that reflect analyst expectations. GIS data therefore play a prominent role in providing typicality information as well as ancillary data to guide the choice of decision rule. Slow but continual progress in the integration of spatial analysis software and existing GIS packages has resulted in a growing number of methods from which to choose when formulating inductive models to map forest change (Eastman et al., 2005). Parametric classification algorithms such as maximum likelihood and minimum distance classifiers are available in standard image-processing software. These methods generally produce repeatable and reliable results, but they assume the input data are normally distributed (Carbonell et al., 1983).

Although a standard statistical method in other applications, such as predictive vegetation modeling, generalized linear models (GLMs) have only been applied recently to land cover mapping and monitoring (Morisette et al., 1999; Schwarz and Zimmerman, 2005). GLMs extend classic multiple regression analyses by allowing a less-restrictive form for error distributions (i.e., nonnormal and nonconstant variance functions) (McCullagh and Nelder, 1989). However, GLMs are less exploratory than other more data-driven methods (e.g., classification trees) and require more subjective model specification, requiring that variable transformations and interactions must be explicitly defined a priori.

Nonparametric classification algorithms, such as machine learning, have more recently been applied to forest characterization and change-mapping applications

TABLE 6.3
Examples of Integrated Remote Sensing and GIS Data Applications in Forest Change/Disturbance Studies

Application	Remote sensing data	GIS data	References
Land cover modification	Landsat TM	Geology, aspect, slope, azimuth, horizon, downhill, uphill, position, catchment, steepness	Lees and Ritman (1991)
	Landsat TM	Aspect, slope, elevation, texture	Levien et al. (1999)
	Landsat TM	Aspect, elevation, slope, vegetation map, fire history	Rogan et al. (2003)
	Terra MODIS	Continuous tree cover	Zhan et al. (2002)
Land cover conversion[a]	Landsat MSS and TM	Aspect, slope, elevation	Parmenter et al. (2003)
	AVHRR	Elevation, precipitation, temperature	Liu et al. (2003)
	JERS-1	Vegetation map	Siqueira et al. (1997)
	Landsat TM	Elevation, slope, timber harvest	S. E. Franklin and Wulder (2002)
	Landsat ETM+	Elevation	Wulder et al. (2004)
	Landsat TM and ETM+	Elevation, slope, aspect	Lawrence and Wright (2001)
	Landsat ETM+	Elevation, slope, aspect, cosine of solar zenith	Carpenter et al. (1999)
Wildfire burn severity	Landsat TM	Elevation	Rogan and Yool (2001)
	Landsat TM	Elevation	Medler and Yool (1997)
	SPOT-2	Aspect, slope	Chafer et al. (2004)
Ice storm damage	Landsat TM, ETM+	Elevation, slope. aspect, total freezing precipitation, and proximity to forest edge	Olthof et al. (2004)
	Landsat TM	Elevation, aspect	Millward and Kraft (2004)
Forest decline	Landsat TM	Slope, aspect	Khorram et al. (1990)
Succession	Landsat TM	Fire history, slope, aspect, vegetation	Peterson and Stow (2003)
	AVIRIS	DEM, vegetation layers	Riano et al. (2002)

[a] Single-date land cover maps were generated as geospatial data for long-term monitoring.

Provide Parmenter et al., 2003, citation.

Provide Carpenter et al., 1999, citation.

Provide Millward and Kraft, 2004, citation.

Provide Riano et al., 2002, citation.

Provide Siqueira et al., 1997, citation.

Provide Lawrence and Wright, 2001, citation.

Provide Chafer et al., 2004, citation.

Provide Peterson and Stow, 2003, citation.

(Gopal et al., 1999). In addition to often producing better results, they allow for data that are not normally distributed and offer greater ease in incorporating ancillary data (Friedl et al., 1999; Skidmore and Turner, 1988). MLAs refer to the application of induction algorithms that analyze information, recognize patterns, and improve prediction accuracy through automated, repeated learning from training data (Carbonell et al., 1983; Malerba et al., 2001). There is a large body of research that demonstrates the abilities of machine learning techniques, particularly classification trees and artificial neural networks, to deal effectively with tasks involving data with high dimensionality because of their ability to reduce computational demands significantly for nonlinear data distributions (Gahegan, 2003). As a result, MLAs have gained acceptance in the context of large-area forest mapping (Friedl et al., 1999; Hansen et al., 1996) given the need for automated, objective, and reproducible classification methods that can handle very large volumes of data across coarse spatial scales (Borak and Strahler, 1999; Gopal et al., 1999; Hansen et al., 2000; Hansen and Reed, 2000; Muchoney and Williamson, 2001). Classification and regression trees have the potential to serve as rule generators for complex forest-monitoring tasks because mapping decisions are transparent and explicit (Rogan et al., 2003). In addition, decision trees can provide a "first cut" rule set as input to an expert system and act as a bridge between automation and expert knowledge.

Expert system (also referred to as knowledge- or rule-based) classifiers are a recently explored alternative to conventional supervised classification. Expert systems typically relate classes to properties through a series of rules representing conditional statements and are favored for complex mapping tasks (X. Huang and Jensen, 1997). Expert system approaches have several important advantages related to their facility for incorporating GIS data in the rule-making (knowledge-generating) process. Unlike many statistical methods, expert systems do not have stringent requirements about data distribution and independence (Quinlan, 1993). Expert systems have been used to incorporate GIS data in several land cover mapping applications (Comber et al., 2004; X. Huang and Jensen, 1997; Levien et al., 1999; Raclot et al., 2005; Rogan et al., 2003). Ehlers et al. (2003) developed an automated procedure for incorporating GIS layers, elevation, and multispectral image data for fine spatial resolution biotype mapping.

Object-based or per-field approaches to forest cover mapping and monitoring appear to be an emerging theme in the GIS science literature (Raza and Kaiz, 2001). Despite widespread use, pixel-based methods for mapping generally do not make use of the spatial and geometric properties of the data (Wulder, 1998). Object-based classification methods allow for the incorporation of contextual information in the mapping process. This type of application enables the segmentation of multispectral imagery into meaningful homogeneous objects, or regions, based on neighboring pixel spectral and spatial values. Although operational examples are rare, case studies involving a variety of remotely sensed data types are becoming more common (Lamar et al., 2005). Wulder et al. (2004) used segmented Landsat-7 Enhanced Thematic Mapper Plus (ETM+) data to estimate stand ages of regenerating lodgepole pine forest stands. Segmentation aided the removal or masking of pixels on the periphery of clear-cuts that consisted of intact trees. Segmented polygons were shown to represent more accurately estimated stand age than forest inventory poly-

gons. Also, Hinton (1999) integrated airborne synthetic aperture radar and vector data representing forest stands of a single species to minimize within-class confusion and produced maps with 8% higher accuracy than a per-pixel method. Spatial errors in the vector data initially resulted in a reduction in map accuracy prior to some additional processing. One substantial drawback of object-based methods is that land cover change may only be detected if a substantial proportion of the object is modified. For example, when the unit of observation is a forest stand, multitemporal changes do not always follow stand delineations (Varjo, 1997). The question of whether stand delineations should be based on acquired images or existing GIS coverages is subject to further investigation.

Validation and Change Analysis

An in-depth understanding of the processes of forest change/disturbance is predicated on the ability to monitor forests accurately over several decades (Lambin, 1999). A need exists for operational methods to assess the quality of large-area change maps. Unfortunately, well-established accuracy assessment methods (i.e., using an independent sample of validation data) that are commonly used at local scales are often not practical at coarse scales. Validation can be based on existing maps. Siqueira et al. (2000) validated a land cover map of the Amazon, based on JERS-1 data, using a combination of physiographic/climate-based vegetation map, local vegetation maps, and advanced very high resolution radiometer (AVHRR)-based land cover maps to estimate an accuracy of 78% (14 vegetation classes). High-quality local-scale maps can be used for large-area validation. Stoms (1996) proposed the use of "maplets" for validating large data sets — maps from local and state agencies for specific sites (e.g., a state park or a project area). While promising, these fine spatial resolution products require careful processing and preparation if they are to be used to validate coarser resolution products acquired by different sensors for different operational mapping needs (Trietz and Rogan, 2004). For example, uncertainty can be introduced into validation results as a consequence of differences between the classification schemes of each map and potential geolocation errors in both products (Fuller et al., 2003).

Define JERS.

Efforts to compare different land cover products hinge on interoperability between remotely sensed and GIS data sets. Inconsistencies between spatial resolutions and land cover classification systems inhibit comparison and generalization between large-area regional monitoring systems and global monitoring systems. Recent work in GIS science has begun to reconceptualize the basis of land cover classification systems by defining classes with formal parameterizations (Ahlqvist, 2004). Land cover classes are viewed as semantic concepts that can be defined by quantitative parameters, such as percentage cover of tree crowns or texture indices. Each class is defined by a collection of fuzzy set membership functions for a specified number of continuous variables that describe the class. Salience weights are applied to specify the importance of each variable to the definition of the land cover class. To address the complexities of having different spatial resolutions in map comparison, Pontius (2002) presented new statistical methods to partition effects of quantity and location in a comparison of categorical maps at multiple spatial resolutions.

CURRENT LIMITATIONS OF FOREST CHANGE DETECTION AND MAPPING STUDIES

Data recorded by remote sensing instruments are valuable for providing information on forest cover conversion and modification but are not always a consistent indicator of discrete change events (Loveland et al., 2002). The detectability and accurate characterization of forest disturbance using remotely sensed data are influenced by the type of disturbance, the magnitude and duration of the modified signal, and natural variability (species/stand/landscape). These factors can often result in high errors of omission and commission in forest change maps. Indeed, map accuracy in land cover change research is typically 15–20% lower than that found in single-date land cover scenarios (Rogan et al., 2003). Figure 6.2 presents the conceptual trade-offs that exist in a forest disturbance mapping scenario. Trade-off considerations of typicality, data characteristics, and the classification/mapping rule become increasingly problematic as landscape heterogeneity increases because the spectral variation caused by forest decline often overlaps with spectral variation caused by topography, species composition, and stand structure (S. E. Franklin and Raske, 1994). For example, large-area mapping/monitoring is especially difficult because any landscape homogeneity at small spatial extents (e.g., a single Landsat image) can transform into heterogeneity at larger extents (e.g., a mosaic of ten Landsat images) (Wulder et al., 2004).

Omission Errors

Problem

Anthropogenic disturbances such as forest conversion to agriculture or urban land use are typically mapped with replicable levels of map accuracy (Seto et al., 2002). When the forest disturbance does not cause an acute alteration in the spectroradiometric or textural properties of the landscape, excessive omission errors are common. For example, Olsson (1995) could not reliably map canopy cover decrease (less than 20–25%) caused by forest thinning using Landsat-5 TM data in a boreal forest because damage did not result in a near-infrared reflectance decrease in excess of 0.015. Similarly, Souza and Barreto (2000) could not reliably detect/map the locations of selective harvest sites in tropical forest, using Landsat-7 ETM+ data, despite having access to detailed field data on timber extraction.

When researchers seek to derive ordinal-scale disturbance information at fine levels of thematic detail (i.e., high, medium, low), detection accuracy is often less reliable for low-impact categories (Coops et al., Chapter 2, this volume; Rogan et al., 2003). Dichotomous categories of forest change/no change can usually be mapped using Landsat-like data with accuracies on the order of 80–90% overall accuracy (Varjo, 1997). Detection of ordinal change/disturbance categories is a more difficult task (Heikkonen, 2004), requiring more stringent requirements for calibrated and corrected satellite data to remove noise. For example, Rogan and Franklin (2001) reported that light wildfire burn severity areas were less reliably mapped than *severe* areas in chaparral woodland because of spectral confusion with unburned vegetation patches. Ekstrand (1990) reported that reflectance in Norway spruce decreased as

EDITOR: Cross reference to Chapter 2.

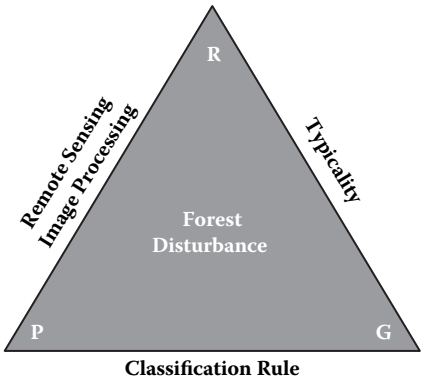

FIGURE 6.2 Diagram illustrating the trade-offs that exist in forest disturbance/change mapping where R = Reality; P = Precision; G = Generality. Typicality (information classes) and spectral classes (remote sensing) are rarely in complete agreement with each other (i.e., R G). Classification (decision) rules make suboptimal choices in the presence of image noise or suboptimal sensor/data/scene models (i.e., P R). Generalization of well-modeled decision rules is rarely possible over highly heterogeneous landscapes/regions/biomes (i.e., P G).

needle loss increased from 10 to 40% due to tissue damage and pigment alterations. Variation in composition and density of forest stands was cited as the cause of low accuracy levels because intercanopy shadowing affected the ability to discriminate between low and moderate defoliation levels and caused spectral differences between areas of similar defoliation conditions. Gemmell and Varjo (1999) reported problems in detecting different levels of timber harvest in a boreal forest caused by variation in tree species composition, type, and understory vegetation. Ciesla et al. (1989) reported confusion between moderate levels of gypsy moth damage and conifer plantations on shaded slopes.

Change detection approaches used to classify the cause of disturbance are problematic in that classes are not mutually excusive and totally exhaustive (Coppin and Bauer, 1996). Further, several authors have found that partial-cut classes often have higher omission errors than clear-cuts (Heikkonen, 2004; E. H. Wilson and Sader, 2002). Higher temporal-spectral variation in peat soils versus mineral soils has also caused confusion in mapping timber harvest (Varjo, 1997). While the radiation ecology of forest understory has been cited as a source of confusion in detecting overstory damage, subcanopy disturbances such as surface wildfires, brush clearing, and floods are largely undetectable because the "disturbance signal" is blocked by the overstory canopy (Rogan and Franklin, 2001). Other confounding influences on the detectability of forest change include the rates of regeneration and recovery, typically determined by climatic factors, plant adaptation to disturbance, and mitigation of impact by resource managers (Coppin et al., 2004).

Solution

Used judiciously, GIS data have the potential to mitigate some of the current limitations of forest change mapping associated with map omission errors. In the first

instance, information about forest cover or soil type could be used to help control for the intrinsic landscape variability that can prevent adequate detection of subtle disturbances (Heikkonen, 2004). GIS data can also provide cues and clues for detection of *cryptic* target features, such as selective harvest in tropical forest, based on information from other scene objects such as the use of roads and log landings (Nepstad et al., 1999; Souza et al., 2005). Second, GIS data can be used directly to provide additional predictive power to a classification algorithm (Eastman et al., 2005). For example, using remotely sensed data alone, one cannot detect a burn scar that occurred underneath a closed forest canopy. Burn detection accuracy, however, may increase if a slope variable is added to the analysis when training data also represent burn locations on certain slope intervals (Rogan et al., 2003). GIS data can thus be used as environmental input variables potentially to serve to fill image data "gaps." From a temporal perspective, Brivio et al. (2002) found digital topographic data useful to overcome the limitation caused by the time lag between the peak of a flooding event and ERS-1 synthetic aperture radar satellite overpass to map flood damage.

Define ERS.

Commission Errors

Problem

Even if the signal of a forest disturbance is strong enough to overcome species-stand variation to be detectable, it can be confused with landscape features having similar spectral properties, resulting in map commission errors. Commission errors are most prevalent in unitemporal change detection studies, in which only postdisturbance images are used, and analysts do not have the benefit of multispectral "from-to" information, common in bitemporal change detection (Coppin et al., 2004). Burn scars are typically confused with asphalt roads and deep, clear water bodies in most environments (e.g., Chuvieco and Congalton, 1988); secondary growth is often mislabeled as pasture (and vice versa) in disturbed tropical forest (Powell et al., 2004); recent timber clear-cuts are occasionally misclassified as senesced meadows in temperate forests (Levien et al., 1999); and heavy levels of gypsy moth damage are confused with fallow fields and talus slopes (Ciesla et al., 1989). Such problems of signature separability typically bias severe or high damage/impact disturbance categories, resulting in "overclassification" in ordinal-scale disturbance maps.

The presence of other disturbance types (current or past) is a second source of commission errors in forest change maps. In chronically modified landscapes, different types of natural and anthropogenic disturbances may spatially coexist and interact over time (Attiwill, 1994; Kittredge et al., 2003; Souza et al., 2005). For instance, the presence of old burn scars in a study area can be misclassified as light burn (Key and Benson, 2002), and ice storm damage to canopy can be confused with selective harvest removal. Further, it has been demonstrated that one type of disturbance can influence the proclivity of a forest stand to future disturbance. Macomber and Woodcock (1994) and Collins and Woodcock (1996) studied the impacts of drought on insect pest mortality in temperate forests. Also, Lindemann and Baker (2002) found forest blowdown sensitive to physical factors such as wind

exposure, aspect, elevation, and forest cover type, while others have cited the significant influence of previous clear-cutting on windthrow (see Coates, 1997; Huggard et al., 1999).

Solution

To mitigate commission errors in disturbance mapping, GIS data can be used to create spatial masks of the landscape features most often confused with the disturbance type of interest (Levien et al., 1999). Objects with low optical reflectance such as water and roads as well as topographic shadows can often be confused with severely disturbed areas such as severe burns. Also, early stage secondary forest growth is often indistinguishable from shrub and scrub vegetation (see Powell et al., 2004). Where multiple disturbances are present or have a high probability of presence, GIS data representing previous disturbance events could be used to reduce the potential confusion. For example, White et al. (2005) applied and an "exclusionary" mask generated from the locations of logged sites, water bodies, and cloud cover to IKONOS-2 images to reduce variability in mapping mountain pine beetle outbreak.

SELECTED APPLICATIONS

Burn Mapping

Detailed burn scar mapping is one of the most challenging applications of remotely sensed data and remote sensing technology (Rogan and Yool, 2001). In addition to the removal of vegetation and exposure of soil, the aftermath of combustion adds new features to a remote sensing scene — charcoal and ash. Forest environments burn with varying intensities (i.e., energy released per unit length of flame front, per unit time), depending on fuel type, fuel load, fuel moisture, and topographic constraints (i.e., slope and aspect) (Pyne et al., 1996). Variation in fire intensity yields variations in burn severity, ranging widely from partial consumption of vegetation cover with little soil exposure or char/ash deposition, to complete consumption of vegetation cover with high soil exposure and char/ash deposition (Pyne et al., 1996; Yool et al., 1985). Consequently, the cumulative effect of a burn is often a heterogeneous mix of remote sensing image scene elements associated with burn severity or damage to soil and vegetation (Clark and Bobbe, Chapter 5, this volume; Rogan and Franklin, 2001; A.M.S. Smith et al., 2005).

EDITOR: Cross reference to Chapter 5.

Several problems make burn severity monitoring difficult using satellite imagery (i.e., at coarse [AVHRR] or finer [Landsat-5 TM] spatial scales). The most commonly reported problem is that burned vegetation patches are often confused spectrally with nonvegetated surfaces with similar spectral signatures (i.e., asphalt roads, deep water bodies). However, the effects of topography and smoke plumes confound these factors. Topographically induced shade caused by illumination differences can create spectral confusion between shaded unburned vegetated patches, shaded nonvegetated patches, and burned patches (Chuvieco and Congalton, 1988). Over large areas, vegetation diversity becomes problematic as it is difficult to assign a label of high, medium, and low damage when vegetation diversity (lifeform) is also spatially

variable (Rogan and Franklin, 2001). Thus, stratification by soil or vegetation would be useful (Vigilante et al., 2004). Several applications to map burn scars have successfully incorporated GIS and remotely sensed data (Chuvieco and Congalton, 1988; White et al., 1996). Medler and Yool (1997) combined composite terrain and Landsat-5 TM imagery in a supervised classification to map wildfire mortality. Error matrices indicated that this amalgam of satellite and ancillary data provided a 40% improvement in accuracy compared to TM data alone. DEMs are not always useful, however, when burn management/containment strategies are contrary to theoretical fire behavior models (Rogan and Yool, 2001).

Pest Infestation

Many methods used for detecting insect defoliation were originally developed to detect forest damage related to air pollution in European forests (Waldsterben) in remotely sensed imagery (Herrmann et al., 1988). Factors contributing to insect pest infestation include drought stress (Collins and Woodcock, 1996); high stand density; species composition, age, elevation, aspect, vigor (S. E. Franklin, 2001); and soil type (Bonneau et al., 1999). Compared to burn mapping, there are fewer operational examples of pest damage mapping using medium spatial resolution data. This is due to the high natural variability in forests affected by pests and the relatively light influence of pest damage on the spectral response of medium-resolution/broadband sensors (S. E. Franklin et al., 2003). For example, Nelson (1983) reported that a moderate pest defoliation category could not be accurately delineated using Landsat MSS data as it was usually confused with the reflectance variability of healthy forest. This problem was also reported by Joria et al. (1991) using both Landsat-5 TM and SPOT-2 data.

To address the previously stated challenges, Williams and Nelson (1986) developed techniques using a Landsat-5 TM Band 5/7 (mid infrared) ratio to delineate and assess forest damage due to defoliating insects; they reported 90% overall accuracy for delineating insect-damaged and healthy forest. The use of a nonforest mask reduced classification confusion with nondefoliated areas in the scene that displayed similar reflectance to defoliated canopy. Rohde and Moore (1974) analyzed single- and multidate Landsat-1 data to detect the impact of gypsy moth. In this early study, confusion of sites with defoliation with agricultural land use, or open-face mining areas in postinfestation imagery only, was minimized using the multidate images. S. E. Franklin et al. (2003) and Skakun et al. (2003) examined mountain pine beetle red attack damage in lodgepole pine stands in British Columbia. Overall map accuracies of 73–78%, using postinfestation Landsat-5 TM data, were facilitated through the stratification of the calibration data set using polygonal forest inventory data. These data were used to reduce the variability in the calibration data based on logical decision rules related to host susceptibility and forest structure. This stratification technique was applied previously to improve classification results of spruce budworm defoliation in western Newfoundland (S. E. Franklin and Raske, 1994).

Wulder et al. (2005) used a polygon decomposition approach to integrate different sources of data (field data, aerial surveys, Landsat images) within a GIS to examine the impacts of mountain pine beetle. Polygon decomposition was imple-

mented by populating forest inventory polygons with the proportion (in percentage) and area (in hectares) of damaged pixels that had been generated from Landsat-7 ETM+ data. Analysis of the combined data revealed that stands of high pine component in the age category 121 to 140 years, with diameter breast heights above 25 cm, and with 66 to 75% crown closures were most susceptible to beetle attack. Younger balsam fir (*Abies balsamea*) stands are more susceptible to spruce budworm defoliation than mature stands. This makes satellite-derived age maps suitable for mapping a determining factor of insect population levels useful in predicting future outbreaks (Luther et al., 1997). Finally, Radeloff et al. (1999) excluded timber clear-cut areas and masked pure stands to detect jack pine budworm defoliation.

Ice Storm Damage

Remote sensing applications in ice storm damage mapping were rare in the remote sensing literature until the 1998 ice storm event, which affected large portions of northern New England in the United States and southern Quebec and eastern Ontario in Canada (Irland, 1998). Ice storm damage to forest canopy occurs at different spatial and temporal scales and results in bending, branch loss, and topping. Damage is often related to canopy architecture, tree size, age, health, and the mechanical properties of the wood itself (e.g., elasticity and rigidity) (Pellikka et al., 2000). Physiographic factors such as elevation and slope influence the depth and duration of ice accumulation (Irland, 1998). Olthof et al. (2004) found that a neural network classifier produced damage maps with higher accuracies than the conventional parametric classifiers when ancillary environmental variables (ice accumulation, elevation, slope, aspect, distance from forest edge) were incorporated into the classification process. Classification accuracy improved from light, medium, to heavy damage categories (19.5%, 44.4%, 77.3%, respectively). Overall damage classification accuracy was approximately 65%. Ice storm damage is indicative of the complexity found when seeking trends related to the influence of environmental factors resulting from a particular disturbance event (e.g., elevation, aspect, slope, and forest type). In reviewing the increasing body of literature on the topic, environmental variables such as "distance to forest edge" played a significant role in damage prediction in some, but not all, studies.

Timber Harvest

Change correct as in references? If not, provide Franklin et al., 2002, citation.

Timber clear-cut detection and monitoring appears to be one of the most successful and reliable applications of remotely sensed data in forest disturbance mapping. S. E. Franklin and Wulder (2002) presented a comprehensive examination of harvest-related change over 15 years using Landsat-5 TM data in the Fundy Model Forest, New Brunswick (Canada). Multitemporal change thresholds (based on Kauth-Thomas wetness) were calculated based on spatial information concerning areas disturbed by clear-cutting, partial harvesting, and silvicultural treatments. Further, GIS inventory data were used to mask all nonforest areas for final forest change mapping. Gemmell and Varjo (1999) reported problems in detecting different levels of timber harvest in a boreal forest caused by variation in tree species composition, type, and

understory vegetation. In addition, when the unit of observation is a forest stand, multitemporal changes do not always follow stand delineations (Varjo, 1997).

Heikkonen (2004) prestratified a boreal forest area based on mineral soil type only to reduce the influence of soil background variation timber harvest mapping. Masks are often applied to eliminate "irrelevant areas", such as water bodies and extreme slopes, from analysis (Wilson and Sader, 2002, p. 7). Saksa et al. (2003) promoted the use of predelineated segments or pixel blocks for image differencing to decrease the number of misinterpreted areas in a study. In this work, a digital forest mask was considered "crucial" to operational applications. Nilson et al. (2001) stated that thinning in boreal forest could result in the appearance of bare soil, cutting waste, and subcanopy vegetation. Heikkonen (2004) found a moderate harvest category (thinning and preparatory cut) least accurate compared to no change and considerable change categories. Selective logging is becoming a major form of disturbance in tropical forests (Cochrane and Souza, 1998). These modifications are often difficult to detect (Coops et al., Chapter 2, this volume). Conway et al. (1996) improved the detection of selectively logged areas using expert knowledge of the topography and soil disturbance patterns of logged tropical forests.

EDITOR: Cross reference to Chapter 2.

CASE STUDY: THE CALIFORNIA LAND COVER MAPPING AND MONITORING PROGRAM

To address the growing threat to forest and shrubland sustainability caused by rapid and widespread land cover change in California, the U.S. Forest Service and the California Department of Forestry and Fire Protection are collaborating in the statewide Land Cover Mapping and Monitoring Program (LCMMP) to improve the quality and capability of monitoring data and to minimize costs for statewide land cover monitoring (Levien et al., 1999). The long-term goals of the LCMMP are to develop a baseline to monitor the amount and extent of forest and rangeland resources, to track forest health trends, and to examine the effectiveness of existing environmental policies. Monitoring data created by the LCMMP quantifies changes to forests, shrublands, and urban areas across 70% of California and provides necessary information for regional assessment across jurisdictional boundaries (Levien et al., 1999). A key advantage of this cooperative program is that monitoring information provides a single consistent source of current landscape-level and site-specific change to the U.S. Forest Service and California Department of Forestry and Fire Protection as well as other interested federal agencies. The LCMMP maps and monitors land cover according to the boundaries of 20 or more Landsat scenes and ecological subsections from the National Hierarchical Framework of Ecological Units (Bailey, 1983). The total area includes approximately 2 million Ha of National Forest Systems lands.

Should this be "Service"?

The data-processing flow of the LCMMP is presented in Figure 6.3. The LCMMP uses Landsat-5 TM and Landsat-7 ETM+ satellite imagery within five-year monitoring periods. Changes in forest, shrub, and grassland cover types are the primary focus of this program, but changes in urban/suburban areas are also mapped (Table 6.4). These change maps are required for regional interagency land manage-

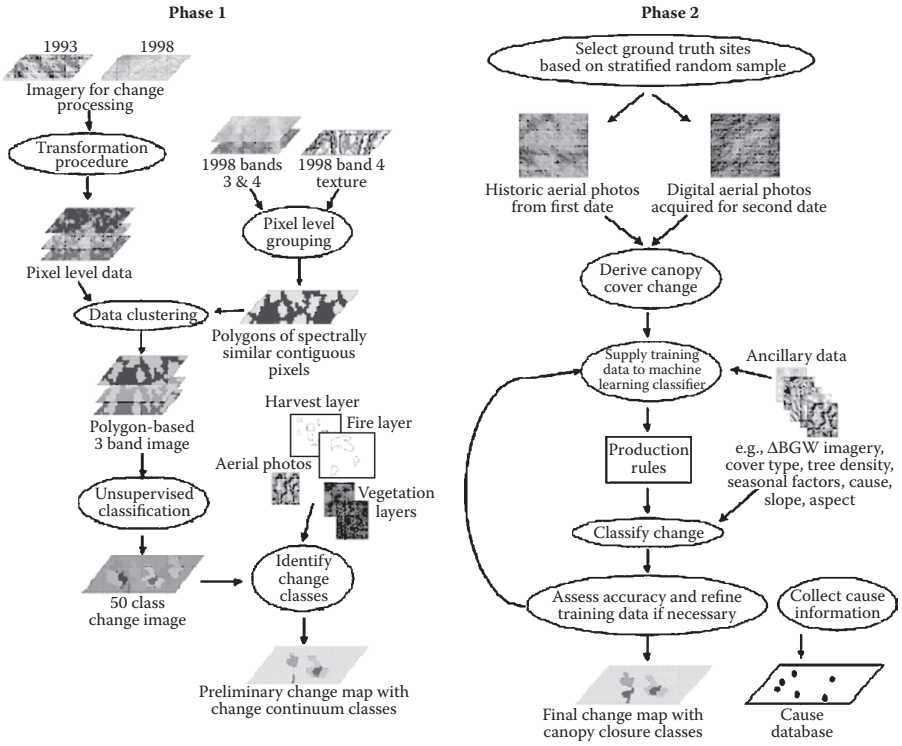

FIGURE 6.3 Overview of LCMMP Phase I and Phase II classification methodology.

TABLE 6.4
Classification Schemes for LCMMP Phase I and Phase II Land Cover Change Maps

Phase I change classes	Phase II change classes
Large decrease in vegetation	–71 to –100% canopy change
Moderate decrease in vegetation	–41 to –70% canopy change
Small decrease in vegetation	–16 to 40% canopy change
	Shrub/grass decrease > 15%
Little or no change	±15% canopy change
Moderate increase in vegetation	+16 to +40% canopy change
Large increase in vegetation	+41 to 100% canopy change
	Shrub/grass increase > 15%
Nonvegetation change	Change in developed areas

ment planning, fire and timber management, and species habitat assessment and for updating existing land cover maps at a low cost per unit area cost (approximately $0.01/Ha) (Levien et al., 1999, 2002).

Landsat imagery that has been geometrically rectified, radiometrically normalized, and subset into processing areas is ready for input into the change-mapping process (Levien et al., 1999). A concurrent process involves preparing and mosaicking ancillary data layers, including vegetation maps based on CALVEG vegetation categories, fire history perimeters, and timber plantation/harvest information. Ancillary data are used both as a masking tool and as a means for stratification to label the change classes and implement the sampling design for field data collection. Image features are then extracted from the Landsat (E)TM data using texture (Band 4) and multitemporal Kauth-Thomas routines. An unsupervised classification is applied to each per-scene change image by CALVEG lifeform category, resulting in 50 change classes per lifeform. Each change class is labeled according to its level of change based on a gradient of change from large decreases in vegetation to large increases in vegetation. The final product from Phase I is a change map containing a gradient of classes that ranges from large decreases in vegetation to large increases in vegetation.

Define CALVEG.

The goal of Phase II is to make a land cover change map representing discrete changes in forest and shrub cover. The change map legend is shown in Table 6.4; it describes three discrete categories of forest canopy cover decrease and two classes of canopy increase. Further, a shrub cover increase and shrub decrease class is used, along with change in developed (urban) areas and no change (±15% canopy change) categories. The ±15% no change class was designed to reduce the confusion between phenological changes and postdisturbance increase classes by allowing for minor increases/decreases in vegetation abundance. Ground reference data are obtained by estimating forest canopy cover change within a five-year time frame using two sets of aerial photographs and in situ information. To calibrate canopy cover estimates from air photos, photo-interpreted canopy cover measurements are compared with those measured in the field. The result of this analysis is a calibration/validation data set portraying classes of canopy cover change, which are then used in the change-mapping process.

An example of the Phase II change map for a pilot study region in southern California is shown in Figure 6.4. A general map accuracy assessment is performed on the land cover change maps. Final products from Phase II include the land cover change map derived from the classifier featuring discrete canopy cover change classes and the GIS database identifying the locations of vegetation change with cause information for coniferous forest, hardwood rangeland, shrub cover, and urban areas. This product is then made available to various national resource agencies for ecosystem management activities (Levien et al., 1999). Related products can be found at: http://www.fs.fed.us/r5/spf/about/fhp-change.shtml.

CONCLUSIONS AND FUTURE DIRECTIONS

"The mapping and measurements of small to medium scale changes over large areas requires levels of precision in mapping which are near impossible to achieve with

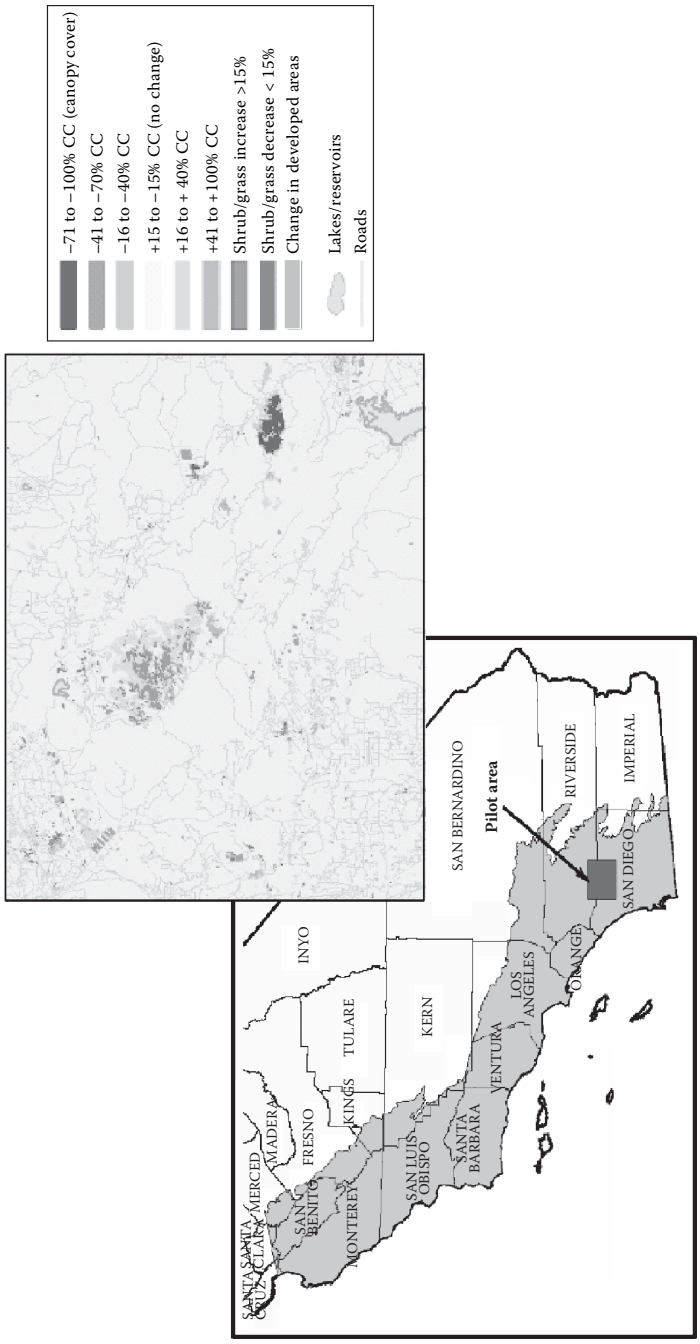

FIGURE 6.4 Overview of LCMMP Phase I and Phase II classification methodology.

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satellite image classifications alone" (Fuller et al., 2003, p. 252). In response to the potentially confounding effects forest disturbances have on single-date mapping applications and the confusion caused by landscape heterogeneity on disturbance mapping applications, recent research has focused on strategies to reduce map confusion using new methods or additional data (Rogan et al., 2003). Advances in GIS and GIS data availability, quality, and type in combination with advances in GIS science research can potentially mitigate the current challenges of large-area monitoring and detailed investigations of subtle forest modifications — two chief impediments to in-depth understanding of the scale and pace of forest change. Smith et al. (2003) stated that digital remotely sensed imagery is soon likely to be a standard instrument in the repertoire of the professional forest manager because the nexus of technology and need has finally occurred. Ustin et al. (2004, p. 689), however, held that "after 30 years of remote sensing, we are still struggling to understand how to interpret the information content in images." To integrate better GIS remotely sensed data and technology with the needs of forest management, we present some important research themes for the near future:

1. Future developments should include expert systems that make better use of multisensor approaches and context-based interpretation schemes (Davis et al., 1991; Fuller et al., 2003).
2. GIS intelligence (e.g., object and analysis models) should be used to automate the forest change/disturbance classification process. In return, GIS objects can be extracted from a remotely sensed image to update the GIS database (Ehlers et al., 2003).
3. Single research methodologies do not suffice for a complete analysis of forest cover change. Instead, a sequence of methodologies is needed that integrates disciplinary components over a range of spatial and temporal scales (S. E. Franklin and Wulder, 2002).
4. Representation of land cover as continuous fields of various biophysical variables for accurate detection of forest degradation (Lambin, 1999).
5. Increased data integration requires further investigation into data accuracy (Ahlqvist, 2004; Fuller et al., 2003).

While there are some outstanding issues to address, data products developed through the integration of remote sensing and GIS enable the capture and representation of disturbance over a range of scales with predictable results. These disturbance products are suitable for further analysis to inform on landscape level dynamics, patterns, and resultant implications.

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