15 Role of Remote Sensing for Land-Use and Land-Cover Change Modeling

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CONTENTS

15.1 Introduction 225
15.2 The Role of Remote Sensing in LULC Modeling 226
15.2.1 Information Obtained from Remote-Sensing Data Sources 226
15.2.1.1 Land Cover 226
15.2.1.2 Land Use 228
15.2.1.3 Landscape Pattern 228
15.2.1.4 Landscape Condition 228
15.3 Use of Remote-Sensing Data in LULC Modeling 228
15.3.1 Scenario Development 230
15.3.2 Driving-Force Analysis 231
15.3.3 Model Parameterization 233
15.3.4 Model Validation 234
15.4 Discussion 234
References 235

15.1 INTRODUCTION

As the impacts of land-use and land-cover (LULC) change on carbon dynamics, climate change, hydrology, and biodiversity have been recognized, modeling of this transformational force has become increasingly important. Given the wide variety of applications that rely on the availability of LULC projections, modeling approaches have originated from a variety of disciplines, including geography, landscape ecology, economics, biology, and others. Initial modeling was often isolated within each discipline, but multidisciplinary modeling frameworks were developed as LULC modelers began to integrate the socioeconomic and biophysical components of LULC change. The empirical and theoretical basis for this work falls within land-use science, and this field documents both land-use and land-cover change, explains the coupled human–environment dynamics that produce the changes, and provides tools for producing spatially explicit LULC models (Mertens and Lambin, 1999; Rindfuss et al., 2004). AQ1

LULC models are data hungry, needing both historical and current land-cover maps coupled with data representing the driving forces of change. Availability of data, especially spatially and temporally consistent data representing those driving forces, is a primary challenge for LULC modeling (Parker et al., 2002; Tayyebi et al., 2008). Site-based observations can be used, but remote-sensing data have several characteristics, most notably repeated synoptic coverage with consistent observation at a relatively low cost, that make them ideal for modeling change. Direct observation

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and mapping of land cover through remote-sensing analysis are critical for identifying and quantifying the major processes of change. This raster (or grid-cell-based) view of the earth's surface offers simplicity, completeness, and efficient processing for analysis (Crews and Walsh, 2009). Empirical diagnostic models of LULC change can then be developed from these observations (Mertens and Lambin, 1999). However, to understand the driving forces of such observed change, these data must be linked to socioeconomic data.

Remote-sensing data play an increasingly important role in LULC modeling. Here we summarize the role of remote sensing in LULC modeling, the use of remote-sensing data in model construction, parameterization, and validation, and the challenges in linking remote-sensing data with analyses of LULC processes.

15.2 THE ROLE OF REMOTE SENSING IN LULC MODELING

Sohl et al. (2010) discussed the need to address several "foundational elements" of LULC modeling, which are as follows: (1) geographic context, (2) regional land-use history, (3) representation of drivers of change, and (4) representation of local land-use patterns. Heistermann et al. (2006) noted four classes of data needed for LULC models, three of which can be derived from or supported by remote-sensing data: (1) current and historical land-use data, (2) environmental data, and (3) scenario data. Several of these foundational elements can be directly informed through the use and analysis of remotely sensed data. In the following section, we discuss remote-sensed information of relevance to LULC modeling and illustrate the discussion with a number of specific applications.

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15.2.1 Information Obtained from Remote-Sensing Data Sources

Most LULC models attempt to untangle the driving forces behind anthropogenic land use, including socioeconomic and biophysical driving forces, but the resulting thematic classification produced by the models often focuses on resulting land covers or a mix of land-use and land-cover "classes." It is important to be clear about the definition of land use and land cover at this stage. Land use refers to how land is used by human beings, whereas land cover refers to the actual vegetative, structural, or other surface cover resulting from a given land use. Agriculture is a land use, but the crop "corn" is a land cover. Remote sensing simply measures the reflective response of the earth's surface, and so it can be used to directly to observe the land cover for a given pixel. Land use must be inferred by linking the measured land cover with ancillary information such as socioeconomic data, field data, or "expert knowledge." Remote sensing excels at detecting surface cover type and condition and provides a number of landscape attributes that can be used by LULC models (Figure 15.1). These are outlined below:

15.2.1.1 Land Cover

Land cover refers to the actual surface cover for a given location (e.g., vegetation type, anthropogenic structure, etc.). Remote-sensing data have a long history of being used for deriving land-cover maps, even before the launch of the first Landsat platform in 1972. Aerial photography served as a primary source of information on land cover before the availability of satellite imagery, and it remains an important source of land-cover information even today (Akbari et al., 2003; Cots-Folch et al., 2007). Aerial photography, which was available before the launch of the first Landsat, remains a valuable tool for analyzing historical LULC change (Gerard et al., 2010; Thomson et al., 2007). With the advent of Landsat and other commercial remote-sensing satellites, land-cover mapping at all scales has flourished. Land-cover information at multiple spatial, thematic, and temporal resolutions has direct relevance to LULC forecast modeling. Consistent, broad-scale, multitemporal land-cover mapping programs such as the United States' National Land Cover Database (NLCD) (Homer et al., 2007; Vogelmann et al., 2001), USGS Land Cover Trends (Loveland et al., 2002), and LandFire (Rollins and Frame, 2006) projects and Europe's CORINE Land Cover (CLC) databases (Büttner et al., 2002; Heymann et al., 1994) are particularly suited for LULC-modeling efforts.

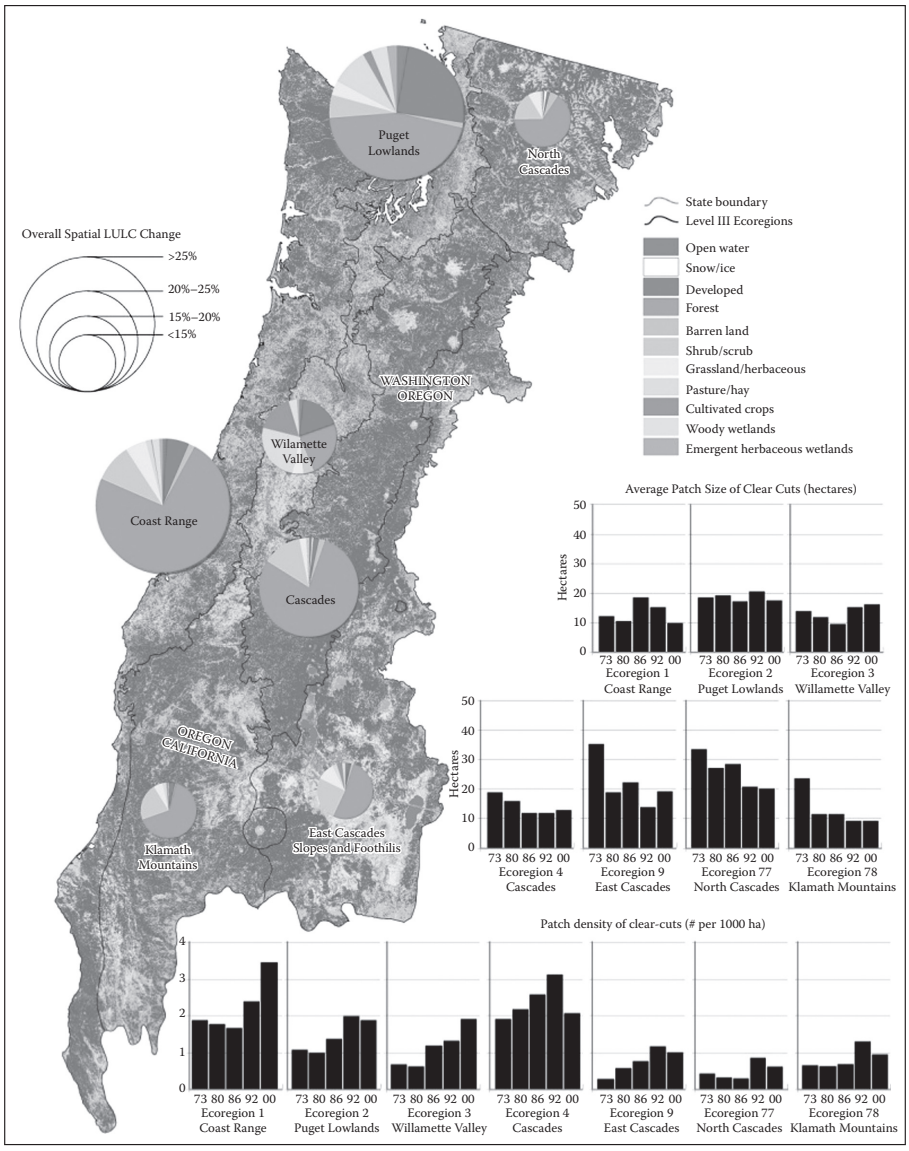

FIGURE 15.1 **(See color insert.)** The area shown covers seven ecoregions (Omernik, 1987; EPA, 1999) in the Pacific Northwest of the western United States, falling in California, Oregon, and Washington. The ecoregions are the Coast Range, Puget Lowlands, Willamette Valley, Cascades, East Cascades, Slopes and Foothills, North Cascades, and Klamath Mountains. All the ecoregions are primarily forested, with varying levels of agriculture, urban, and other land uses. The map shows data from the 2001 National Land Cover Database (NLCD) (Homer et al., 2007) derived from Landsat thematic mapper (TM) and enhanced thematic mapper plus (ETM+) data at a spatial resolution of 30 m. The pie charts represent two sources of important LULC data. Land-cover composition is characterized by the relative size of each "wedge" and is based on NLCD data. The size of the pie charts reflects the amount of land that experienced changes in LULC as measured by the USGS Land Cover Trends project (Loveland et al., 2002). The extent of land area that changed at least once between 1973 and 2000 varies considerably across the seven ecoregions, including ecoregions with similar land-cover compositions. The changes in LULC reflect variability in the biophysical conditions, land ownership and management, and the impact of regional and national policy among other drivers. LULC change data, such as those presented here, are most readily obtained through examination of historical satellite imagery and aerial photographs. The size and density of forest clear-cuts for the seven ecoregions are displayed in a series of bar charts. Landscape metrics such as these are useful for a wide range of ecosystem assessments and are immediately available through examination of remotely sensed data.

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15.2.1.2 Land Use

Unlike land cover, which can be directly observed and monitored from remote-sensing data, land use typically must be inferred through a combination of remote-sensing observation, regional and local knowledge (including field observation), and other ancillary information that links a given land cover in a region with a given land use. As with the mapping of land cover, use of remote-sensing data to assist in the creation of spatially explicit maps of land use has had a long history. Marschner (1950) linked interpreted aerial photography with field notes and statistical summaries to produce the first continental scale, moderate-resolution map of major land uses in the United States. Marschner's basic paradigm is still widely utilized; it uses field surveys, regional knowledge, and other information to infer land use from land-cover observations made from remotely sensed imagery. For example, Brown et al. (2008a) used a combination of MODIS imagery, land-cover classification information from the 2001 NLCD (Homer et al., 2007), and county-level irrigation statistics to create a land-use map of irrigated cropland. Millette et al. (1995) advocated linkages between remote-sensing data, ground truthing, fieldwork, and personnel interviews to provide information on land-use and land-management practices for three villages in Nepal.

15.2.1.3 Landscape Pattern

Spatial patterns of LULC change are regionally unique and dependent on both physical and cultural factors (Gallant et al., 2004). Monitoring and characterizing spatial patterns of LULC change are vital for understanding and predicting LULC change (Petit et al., 2001). Within the field of landscape ecology, modeling of spatial patterns of LULC change needs to be improved (Wu et al., 2008), but this cannot be done without information on current and historical landscape patterns and the driving forces behind the patterns. Remote-sensing information is widely used to analyze landscape pattern. Typically land use and/or land cover is mapped from remote-sensing data and then processed using separate software such as FRAGSTATS (McGarigal et al., 2002) to analyze spatial patterns (Silva et al., 2008; Wang et al., 2009).

15.2.1.4 Landscape Condition

Remote sensing also has the ability to map and monitor changes in surface conditions, which are not related to a direct change in land cover or land use, most notably that of vegetation condition. Long-term datasets such as those provided by the Landsat sensor since the 1970s are particularly valuable for monitoring and understanding changes in vegetation condition (Vogelmann et al., 2009; Wallace et al., 2006). These are complemented by higher temporal resolution sensors such as MODIS, which can map within-season changes in condition (Brown et al., 2008b; Gu et al., 2008; Reeves et al., 2001). Active sensors such as LIDAR or RADAR have the ability to obtain measurements of land surface at any time or season and are also often used for monitoring landscape condition. Together, these sensors have the ability to assess a wide array of landscape condition metrics. Trends in the normalized difference vegetation index (NDVI) or other similar indices are often used as a proxy measure of vegetation condition (Al-Bakri and Taylor, 2003) and for analysis of the impact of drought (Liu and Kogan, 1996; Peters et al., 2002). Active sensors excel at measuring soil moisture (Njoku et al., 2002), canopy height, and forest structure (Lim et al., 2003; Means et al., 2000). Although not many LULC models directly forecast changes in landscape condition, this information can potentially be used within many LULC-modeling environments.

15.3 USE OF REMOTE-SENSING DATA IN LULC MODELING

Historical and current sources of remote-sensing information are obviously quite important for measuring and monitoring changes in landscape parameters. Table 15.1 provides a summary of major categories of spatially explicit LULC models, the majority of which rely directly on remote-sensing information. Data describing changes in land cover, land use, landscape condition, and/or landscape pattern are relevant to a number of associated modeling

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TABLE 15.1
Most Commonly Used Methodologies for Producing Spatially Explicit LULC Projections

Category	Summary	Examples
Markov chain	• Probabilistic state-transition models, with LULC at time $t + 1$ strictly a function of LULC at time t • Transition rules for a given LULC type are often dependent on historical transition probabilities • Transition probabilities typically independent from status or dynamics of adjacent cells	• Muller and Middleton (1994) • Petit et al. (2001) • Coppedge et al. (2007) • Tang et al. (2007)
Geostatistical—empirical	• Development of suitability or probability maps for modeled LULC types to guide placement and location of LULC change • Regression-based analyses often used for development of probability surfaces • Artificial neural networks (ANNs) one subcategory	• GEOMOD—Hall et al. (1995); Pontius et al. (2001) • CLUE—Verburg et al. (1999b, 2008) • FORE-SCE—Sohl et al. (2007); Sohl and Sayler (2008) • Land Transformation Model—Pijanowski et al. (2002); Tang et al. (2005)
Cellular automata	• Spatial-temporal extension of Markov transition models • State-transition model with neighborhood component • Transition rules defined by current state of a cell, but also by status of neighboring cells	• SLEUTH—Claggett et al. (2004); Xibao et al. (2006) • Walsh et al. (2006) • Ozah et al. (2010)
Agent-based	• Recognizes and attempts to model the role of human decision-making in LULC change • Models behavior and interaction of "agents" (individuals, businesses, governmental bodies, or other entities with power to influence change) • Agents influence LULC change at a given location • LULC patterns emerge from interactions between human and natural processes	• MR. POTATOHEAD—Parker et al. (2006) • PALM—Matthews (2006) • SAMBA—Castella and Verburg (2007) • Valbuena et al. (2010)
Integrated	• Integration of multiple modeling approaches and/or frameworks • May include tightly coupled models with significant feedback or loose model coupling focusing on passing data between models • Advantage of potentially incorporating both spatial and aspatial modeling approaches • Typically include econometric or other economic modeling framework	• IMAGE—Alcamo et al. (1998); Strengers et al. (2004) • Verburg et al. (2008) • Jansson et al. (2008) • Moreira et al. (2009)

Note: This table is not all-inclusive. Aspatial modeling frameworks are not included, as they are less likely to directly incorporate remote-sensing data. Model names are noted under "Examples," where appropriate. For additional discussion of LULC modeling types, see Irwin and Geoghegan (2001), Agarwal et al. (2002), and Matthews et al. (2007). All of the aforementioned methodologies often rely on remote sensing information.

fields including scenario development, driving-force analysis, model parameterization, and model validation.

15.3.1 Scenario Development

Scenarios of future land conditions are an important tool for a variety of research themes, including land-use impacts on greenhouse gas emissions and climate change (Strengers et al., 2004), biodiversity (Leadley et al., 2010; Sala et al., 2000), and hydrologic change and water availability (Ray et al., 2010; Wilk and Hughes, 2002) (Figure 15.2). The ability to blend thematically rich narratives describing future conditions with traditional quantitative results stimulates scenario users to think "outside the box" when considering complex human–environmental systems. Several large global environmental assessments have adopted a scenario-based approach. The Intergovernmental Panel on Climate Change (IPCC) defined scenarios as "images of the future that are neither projections nor forecasts" (Nakicenovic et al., 2000) while the Millennium Ecosystem Assessment defined scenarios as "plausible and often simplified descriptions of how the future may develop based on a coherent and internally consistent set of assumptions about key driving forces and relationships" (Carpenter et al., 2005). Alcamo and Henrichs (2008) proposed the following definition: "A scenario is a description of how the future may unfold based on 'if-then' propositions and typically consists of a representation of an initial situation and a description of the key driving forces and changes that lead to a particular future state."

Regardless of the definition preferred, LULC scenarios require two things: knowledge of present conditions and an understanding of how drivers of change interact to create historical landscapes.

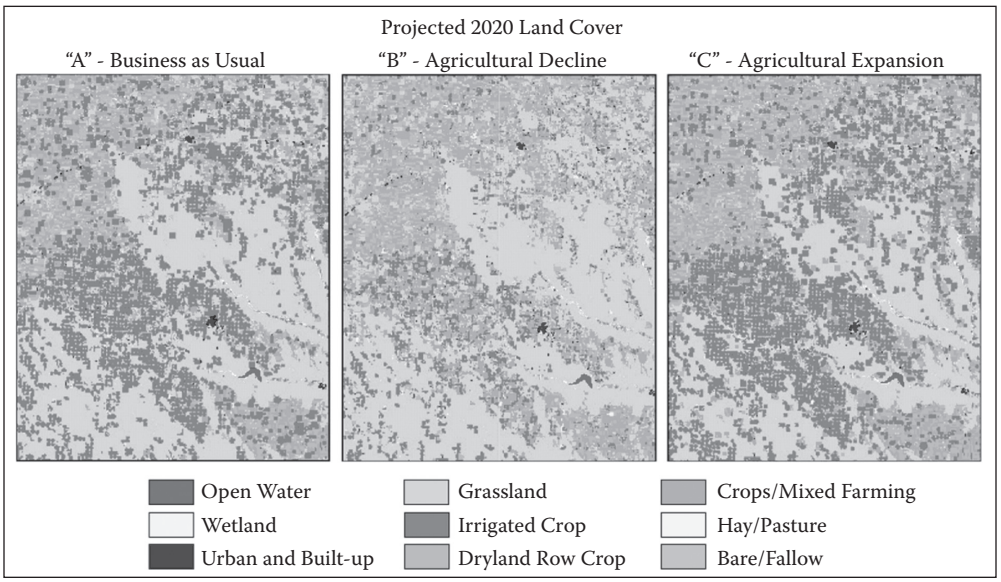

FIGURE 15.2 **(See color insert.)** Scenarios are a vital component of LULC modeling, allowing the exploration of multiple possible futures and resultant impacts on ecological processes. Remote sensing both directly and indirectly informs the construction of viable LULC scenarios through (1) construction of regional landscape histories, (2) examination of LULC patterns, and (3) exploration of linkages between historical LULC change and socioeconomic and biophysical driving forces. Each of these three components was used to develop scenarios and model 2020 LULC for a portion of southwestern Kansas, in the central United States (Sohl et al., 2007). Scenario A depicts a business-as-usual scenario. Scenario B depicts a scenario of low precipitation and declining groundwater availability, leading to agricultural decline. Scenario C depicts a scenario of increased precipitation and a more efficient utilization of groundwater, leading to agricultural expansion. The modeled scenarios were used to examine the impacts of LULC change on regional weather and climate variability.

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LULC scenarios also critically need a baseline map, and irrespective of scale, remotely sensed data have a considerable advantage over survey and field-based methods for deriving such a product. Perhaps even more important is the use of remote-sensing data for developing LULC histories. LULC histories "expose the evolutionary patterns of a specific landscape by revealing its ecological stages, cultural periods, and keystone processes" (Marcucci, 2000). Specifically, LULC histories quantify LULC change over a sufficiently long timescale to illuminate relationships between driving forces such as population growth, economic development, and technological innovation and LULC change. The NLCD (Homer et al., 2007) and Land Cover Trends (Loveland et al., 2002; Sleeter et al., 2010) projects in the United States, the CORINE project in Europe (Büttner et al., 2002; Heymann et al., 1994), and the land-cover change component of Australia's National Carbon Accounting System (Furby, 2002; Waterworth et al., 2007) all rely on historical data from the Landsat archive to map and characterize LULC change. Identifying the rates and types of historical LULC change occurring within socioeconomic and biophysical settings offers the basic understanding from which we can construct alternative visions of the future. Combining the quantitative land-use histories with our understanding of the processes that drive change provides a powerful foundation from which we can develop alternative scenarios based on predefined assumptions about the interaction of various drivers of change.

Scenario development can also include simple projections of historical rates of LULC change. Verburg et al. (1999a) simulated land-use conversions in China using a scenario based on present land-use dynamics. Many LULC-modeling efforts focus on establishing a single reference condition, usually based on extrapolation of historical trends, while modifying certain LULC types to test the hypothesis about future impacts. For example, Kok and Winograd (2002) developed a "base" scenario established by extrapolating historical LULC trends, while using "optimistic" and "natural hazard" scenarios to test LULC response under extremely favorable and unfavorable conditions, respectively. While being relatively simple in design, these types of scenario are still dependent on LULC histories, which are based primarily on satellite observations.

15.3.2 Driving-Force Analysis

One of the great challenges in LULC modeling, and in remote sensing, is the ability to "socialize the pixel" (Geoghegan et al., 2008), linking social science analyses with remotely sensed data. Increasingly, spatially explicit LULC studies using remote sensing have an ultimate goal of not only analyzing the location and type of land-use change but also identifying the primary driving forces of that change (Chowdhury, 2006). Those LULC models that link remote-sensing observations with ground-based social data can greatly improve our understanding of the determinants of LULC change (Rindfuss and Stern, 1998). Generally, remote-sensing data are used in combination with ancillary information on the human decision-making process to understand the cause–effect relationship between driving forces and LULC change. Governmental policy, for example, can have a major impact on LULC change, but remote sensing cannot directly observe and monitor the policy. What remote sensing can do is examine the effects of the policy on land use, allowing LULC modelers to develop qualitative and quantitative relationships between a policy driver and impacts on LULC change. Remote sensing can be used to quantify the effects of a national policy such as the Conservation Reserve Program (CRP) of the United States, which pays farmers for converting environmentally sensitive lands to natural vegetative cover or examining land-use effects of local policies such as property taxation, zoning, or land ownership (Rindfuss and Stern, 1998) (Figure 15.3). Similarly, it can be used to deduce the effects of climate change on vegetation structure or condition (Ingram and Dawson, 2005; Stow et al., 2004).

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Information on population distributions is used in a wide variety of LULC models. Census data can provide detailed information on population characteristics but are not available globally and vary greatly in consistency and accuracy. The LandScan database (Dobson et al., 2000) uses night-time-lights data from the Defense Meteorological Satellite Program (DMSP) (Elvidge et al., 1997)

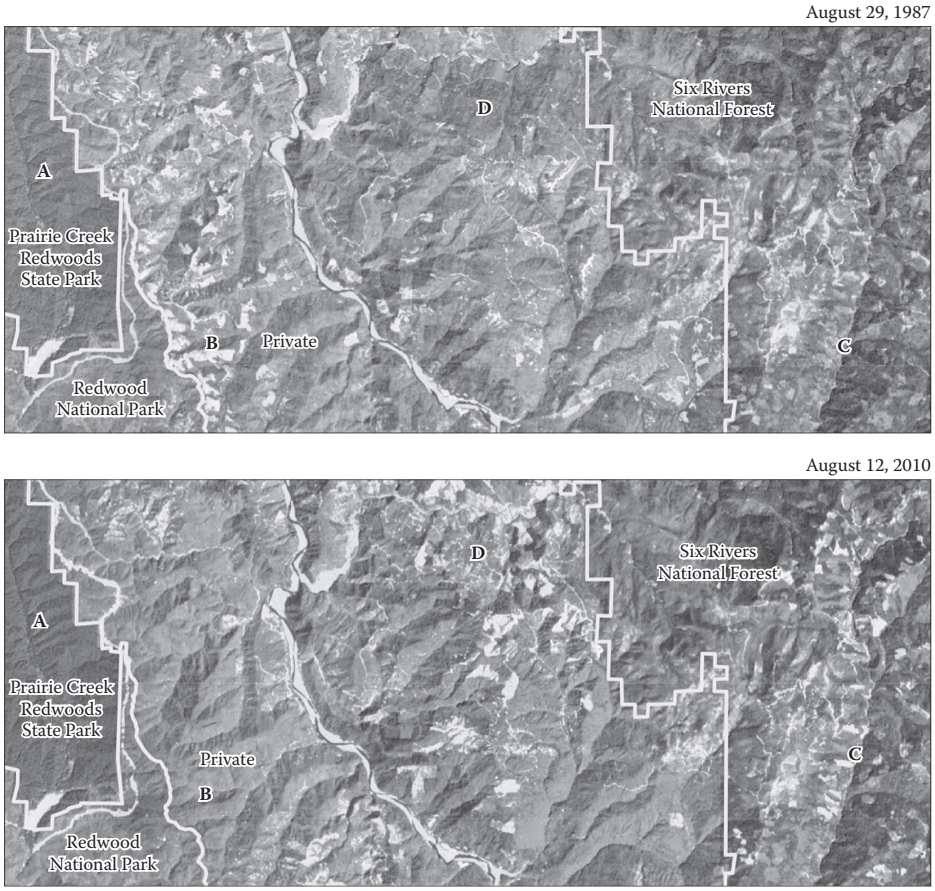

FIGURE 15.3 **(See color insert.)** Two Landsat TM images acquired on August 29, 1987 (top) and August 12, 2010 (bottom). Both images are of the same region in northern California, covering parts of Humboldt and Del Norte counties. The images use visible and near-infrared bands to depict vegetation in hues of red. Dense old-growth conifer stands appear dark red, whereas recent clear-cuts appear bright. Dimensionally, the images are approximately 30 km from east to west and 13 km from north to south. The images span three major land ownership types. Redwood National Park is in the west and is most easily recognized by the large contiguous stand of old-growth redwoods found in Prairie Creek Redwoods State Park. In the eastern portion of the images is Six River National Forest (SRNF). SRNF is managed for multiple uses, including timber harvest. In the center of the image is a large swath of private land holdings along the Klamath River. Cutting on private lands generally occurs in relatively large, often contiguous patches, while SRNF is characterized by a smaller more dispersed pattern of cutting. No cutting is evident in the National Park. Cutting also seems to have accelerated in this area on both private and public lands. Satellite imagery, such as those presented here, are extremely useful for mapping and characterizing changes to landscapes, which provide the foundational understanding for LULC modeling efforts. In this example, land ownership is an important driver and constraint on LULC change and should be considered in any modeling effort.

and remote sensing-based land-cover and topography data in conjunction with census data and other ancillary data sources to produce global maps of population. Similarly, data on roads and other transportation infrastructure are widely used in LULC modeling, but reliable GIS data are often not available. Remote sensing can provide either direct observation of transportation networks or can be used to deduce transportation network extents by mapping associated land-use changes (Bong et al., 2009; Lin et al., 2009). Such remote sensing-based "proxy" datasets are invaluable for LULC models that require spatially explicit socioeconomic data for analyses and modeling of driving

force. Other approaches attempted to establish more direct links between remote-sensing data and social science. McCracken et al. (1999) linked remote-sensing data with survey-based household property-level data to examine agricultural land-use strategies, and Silva et al. (2008) proposed a quantitative method to associate individual patches of land in a remote-sensing image with specific agents of change.

One of the most common uses of remote-sensing data for analyzing driving forces lies in regression-based approaches commonly used for empirical-/statistical-based modeling. Remote-sensing data are commonly used as sources of data for both the dependent variables (LULC type) and independent variables (topographic variables, climate variables, landscape structure information derived from LULC data, etc.) used in regression analyses meant to produce probability-of-occurrence or suitability maps for LULC and LULC change. For example, Verburg et al. (2006) used SPOT imagery along with data on slope, elevation, road access, population density, and market accessibility to develop probability surfaces for analyzing land-use change in the Philippines. Similarly, Sohl and Sayler (2008) used Landsat-derived LULC data from the NLCD project (Homer et al., 2007) and a series of spatially explicit independent variables to produce regression-based probability surfaces to model the placement of LULC change. Brown et al. (2002) used a generalized additive model rather than logistic regression to model forest change in Michigan, using a time series of LULC data derived from Landsat MSS to parameterize the model. Not only are the base LULC data from projects like these often derived from remote-sensing data, but so are many of the independent or ancillary variables. Information on landscape structure, topography, "distance to" measures (e.g., distance to roads), and other independent variables typically used in regression-based approaches often have a remote-sensing origin.

15.3.3 Model Parameterization

Many modeling frameworks depend directly on consistent, historical remote-sensing data for model parameterization. The SLEUTH model is typically parameterized and calibrated with patterns of historical LULC change, with the historically derived parameters driving the modeling of future urban growth patterns (Claggett et al., 2004; Silva et al., 2002; Xibao et al., 2006). Model calibration is also built on a series of spatial metrics, and several of these parameters rely directly on remote-sensing data. Artificial neural net (ANN) models also typically rely on historically mapped LULC information, as well as other ancillary spatial data, for model parameterization and calibration. The Land Transformation Model, for example, develops spatially explicit predictor layers based on how neighborhood effects, patch size, distance measures, and site-specific characteristics affect LULC transitions, with these measures typically derived from remotely sensed data sources (Pijanowski et al., 2002; Tan g et al., 2005). Other models, such as GEOMOD (Hall et al., 1995) and FORE-SCE (Sohl and Sayler, 2008) also use current local pattern information to parameterize and model future LULC change.

Many modeling frameworks rely on remote-sensing data for establishing transition rules and transition probabilities, with mapped historical LULC often driving model parameterization. Petit et al. (2001) used a temporal series of SPOT data to analyze historical LULC change in southeastern Zambia and provided transition probabilities for a Markov chain model. Walsh et al. (2006) used remote sensing to parameterize a CA-based agricultural change model in Thailand, using time series land-cover information interpreted from Landsat TM and MSS images to define state and transition rules. Wu et al. (2006) used LULC information derived from Landsat data between 1986 and 2001 to establish transition probabilities in a first-order Markov-chain model for modeling urban development in Beijing, China. Coppedge et al. (2007) used aerial photography to analyze historical patterns of LULC change in the grasslands of Oklahoma, information that was used to populate transition probabilities and decision rules in a Markov-chain model. Tang et al. (2007) used both changed LULC area (derived from Landsat) and neighborhood LULC information to construct transition probabilities for a Markov-chain model. The FORE-SCE model used historical

LULC information from the USGS Trends project (Loveland et al., 2002) to establish conversion elasticity parameters, a parameter governing transition probability for a given LULC change (Sohl et al., 2007).

15.3.4 Model Validation

Model validation remains an underdeveloped component of LULC-modeling science. The problem for LULC model validation lies more often with the availability of data rather than with suitable validation techniques, as several techniques and tools for validating LULC models have been developed (Chen and Pontius, 2010; Pontius and Petrova, 2010; Visser and de Nijs, 2006). Validation data obviously are not available for modeled future dates, so LULC modelers typically rely on modeling a historical period to perform model validation. Traditional accuracy assessment for one-point-in-time LULC classifications is often made by using aerial photography or another high-resolution remote-sensing source and developing rigorous, pixel-based accuracy assessments. Ray and Pijanowski (2010) used a similar procedure to validate model output for a backcasting application in the Muskegon River watershed in Michigan, using black-and-white aerial photography to interpret sampled validation points for assessing model output.

However, such pixel-by-pixel accuracy assessments are often less desirable choices for LULC-modeling applications, owing to path-dependence and the inherent stochasticity of LULC-modeling processes (Brown et al., 2005). LULC modelers often rely on the validation of landscape patterns rather than on pixel-by-pixel accuracy assessments where the model fit can be determined by the proportion of pixels correctly predicted in a local neighborhood (typically at multiple resolutions) or by comparison of generated landscape metrics between reference and modeled LULC. Brown et al. (2005) calculated edge density, patch size, and other landscape metrics from interpreted LULC to look at a model fit between an agent-based model and reference maps. Castella and Verburg (2007) used LULC maps interpreted from SPOT imagery to assess a CLUE-S model application in Vietnam, using a multiresolution neighborhood validation procedure (Costanza, 1989).

15.4 DISCUSSION

Remote-sensing data and analyses are a vital component of many LULC-modeling efforts. Given the reliance on remote-sensing data for informing LULC models, a primary concern for modelers is continued availability of consistent data. Heistermann et al. (2006) noted that a major problem in LULC modeling was the availability of spatially explicit time series data, while Rindfuss et al. (2004) stated that it was often impossible to obtain consistent, cost-effective, spatially and temporally relevant historical remote-sensing data for supporting land-change science. Crews and Walsh (2009) noted the extreme importance of continued development and maintenance of consistent satellite sensors and databases, with timely data delivery at reasonable prices. Sellers et al. (1995) noted that consistent land-cover data was one of the highest priorities for Land Science, with Herold et al. (2006) even advocating for adoption of a single standard land-cover legend. Even when synoptic, consistent data are available from remotely sensed sources, issues regarding data quality and consistency can strongly affect modeling results. Programs such as the USGS Land Cover Trends project (Loveland et al., 2002) or CORINE (Büttner et al., 2002) certainly have shown their ability to inform LULC modeling, but consistent databases of LULC change are often not widely available, and there is no guarantee of existing programs continuing. Continuance of the remote-sensing programs such as Landsat, as well as consistent LULC mapping and monitoring programs, is vital to the growth of land-change science and LULC modeling.

Continued improvements must also be made in linking remote sensing with the socioeconomic driving forces of LULC change. LULC modelers recognize the human dimension of change, but translating that recognition into sound, integrated theory has been a struggle. Linking pixel-based remote-sensing data with human decision making remains a primary challenge (Matthews et al.,

2007; Rindfuss et al., 2004). McNoleg (2003) stated that the issues were "unbridgeable" for social scientists to utilize raster data models and remote-sensing data, whereas Crews and Walsh (2009) stated that the problem was far too often choosing between "people and pixels." However, given their advantages, remote-sensing data remain too attractive to be dismissed, even for LULC models originating in social sciences. Remote-sensing platforms are built to measure physical phenomenon, and the typical unit of measure, the pixel, typically has no inherent meaning for the socioeconomic driving forces of LULC change. Although these socioeconomic driving forces are typically not directly measurable from remote-sensing platforms, LULC modelers do often develop proxy datasets from remote-sensing data that represent observable effects of social driving forces. Whether it is through the development of proxy datasets or through more direct links between remote-sensing data and the social sciences, it will be difficult for LULC modelers to move away from empirically based modeling systems to true process-based models without developing cost-effective, synoptic socioeconomic datasets that represent the social aspects of LULC change.

LULC modelers must continue to move from being passive users of remote-sensing data to vital team members for planning remote-sensing missions. The temporal, spatial, spectral, and radiometric resolutions of sensors directly affect our ability to map LULC change and monitor LULC processes. Spatial resolution of data alone has a very large impact on LULC-modeling processes and results (Silva and Clarke, 2002), with the driving forces of LULC change extremely dependent on scale. A model such as the aforementioned SLEUTH is extremely dependent on the availability of high-quality historical data on urban growth, but even SLEUTH users note the difficulty in accurate extraction of urban features from Landsat and other remote-sensing data sources (Claggett et al., 2004; Silva and Clarke, 2002). LULC modelers must stay engaged with the remote-sensing community to ensure availability of consistent, suitable remotely sensed data for analyzing LULC and LULC processes.

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AQ1: Please note that the last two sentences in the first paragraph have been deleted as these are the repetition of the sentences given earlier in the same paragraph. Please confirm.
AQ2: Please confirm the edits to the sentence "This raster (or grid-cell-based)…"
AQ3: Please check clarity of the phrase "can be directly informed…" in the sentence "Several of these foundational…"
AQ4: Please provide complete reference details for cross-reference "Geoghefan et al., 2008" in the reference list.
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