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Adequate data of known accuracy are critical to advancing the field of landscape ecology

2.1 Introduction

The science of landscape ecology is especially dependent on high-quality data because often it focuses on broad-scale patterns and processes and deals in the long term. Likewise, high quality data are necessary as the basis for building policy. When issues, such as climate change, can induce international political and economic consequences, it becomes clear that providing high-quality, long-term data is paramount. It is not an accident that this chapter is positioned near the front of this book. Of the priority research topics presented in this book, this is the most pervasive across other topics because the availability of high-quality data limits progress in other realms. Be it historic land-use data needed to understand the dynamics of land-use change, the independent data of varying scales needed to assess scaling phenomena or test new metrics, the socioeconomic/cultural data needed to integrate humans into landscape ecology, or the biological and population data needed to evaluate ecological flows, the quality of raw data, metadata, and derived data products is critical to the core of landscape ecology. For each of these key topics and perspectives, the availability and quality of data will affect research results and practical recommendations.

2.2 Data advances in past two decades

It has been two decades since the 1983 workshop that many say established the landscape ecology field in North America (Risser *et al.* 1984). It was attended by many who have and still contribute to the field (e.g., Barrett, Botkin, Costanza, Forman, Godron, Golley, Hoekstra, Karr, Levin, Merriam,

Key Topics in Landscape Ecology, ed. J. Wu and R. Hobbs.

O'Neill, Parton, Risser, Sharpe, Shugart, Steinitz, Thomas, Wiens, and also a rookie named Iverson). From a scanty list of databases available, this group identified several databases with spatial components useful in landscape ecology: aerial photos; Landsat MSS; biological sampling schemes; and statistical measures of demography. They also identified several problems requiring attention: merging data from multiple sources with various levels of precision, resolution, and timing; choosing display formats appropriate for various uses and without distortions; the need for systematic or stratified field sampling in a heterogeneous universe; and decisions about the appropriate resolution for a particular problem. Researchers still struggle with these problems.

It may be useful to remind ourselves, especially our younger readers, where we were technologically with respect to data acquisition and manipulation two decades ago. I will relay what it was like for me. I was hired by Paul Risser in late 1982 to help develop the Illinois Lands Unsuitable for Mining Program to ensure lands of particular value were deemed "unsuitable" for surface mining. Risser had the foresight to identify that the new technology called "GIS" might be appropriate to do analysis of multiple mapped features. We hired Environmental Systems Research Institute (ESRI) to help us, and we became ESRI client number 12. Risser also believed it important that the GIS technology be made available to scientists, not just computer geeks. So I and my colleagues of various scientific bents spent three weeks in Redlands, CA training with the developers (ArcInfo 2.1 at the time), and the company president, Jack Dangermond, would take us during break to the orange orchard on the property to pick a few oranges. Subsequently, Illinois was the first state with full, integrated vector GIS at 1:500K. Prior to this time, most GIS work was performed with raster processing, using paper print-outs with different symbols for different classes within the matrix. Often entire walls were plastered with these print-outs to get the overall view of the study area. Several people from the Oak Ridge National Laboratory were creating and manipulating county-level data sets for the conterminous United States (Klopatek *et al.* 1979, Olson *et al.* 1980).

ArcInfo 2.1 was vector, but the hardware and software was limited. For data, we had a statewide digitized map of pre-European settlement vegetation (Anderson 1970) and the Land Use Data Acquisition (LUDA) data from the US Geological Survey (Anderson *et al.* 1976), vintage late 1970s. With these, we could assess long-term vegetation changes (Iverson and Risser 1987) and the attributes related to these landscapes (Iverson 1988). At that time, a simple overlay process would run all night; in fact, my colleagues forbade me to run those overlay batch jobs during the day because the shared computer system (which filled a room) would slow to a crawl or crash with more than a few jobs running simultaneously. I "divided" the state into many chunks because the software could not handle so many arcs.

Other characteristics of the time include the absence of ArcView, GRID, FRAGSTATS, CDs, zip drives, disk drives bigger than 300 MB (and these occupied 1 m^3). We had just advanced to 1.4 MB diskettes, and nine-track tapes were the main means of data dispersal. There was no internet and no email. With remote sensing, there was no SPOT, MODIS, radar, hyperspectral data, or any other satellite data besides Landsat MSS and the beginning, experimental phase of Landsat TM and AVHRR. I was privileged to be an early NASA principal investigator, funded to use forest plot data, TM, and AVHRR in scaling forest cover (Iverson *et al.* 1989a,b) and productivity (Cook *et al.* 1987, 1989). However, we had to use small pieces of the Landsat scenes, often only 512×512 pixels.

Civilian GPS units became available in the late 1980s. There were few satellites and few base stations so we had only a few hours of sufficient satellites and we had to do differential post-processing from a station more than 200 km away. Of course, selective availability was the norm until May 2000. There were essentially no spatial statistics or metrics for landscapes other than basic patch area/perimeter metrics. When Krummel *et al.* (1987) published on the value of the fractal, it opened the door to a flood of landscape metrics, including many by the same group in the following year (O'Neill *et al.* 1988). Gardner *et al.* (1987) also first published on neutral models to help assess landscape pattern. GIS-based habitat or suitability models had appeared earlier (e.g., Hopkins 1977, Spanner *et al.* 1983, Iverson and Perry 1985, Donovan *et al.* 1987, Risser and Iverson 1988), but spatially explicit simulation models did not begin to emerge until the later 1980s (e.g., Turner 1988, Turner *et al.* 1989, Costanza *et al.* 1990). We have, indeed, come a long way in the way we acquire and process data.

2.3 Current status

Technology and data sources have perhaps advanced at the scale of computer speed according to Moore's Law, which states that the number of transistors in computer chips will double every 18 months (Moore 1965). However, the people available to analyze these data do not double at this rate, so the workload for all landscape ecologists must necessarily nearly double every 18 months as well. (Not really, but it seems like it sometimes.) Nonetheless, data and ways to acquire data are plentiful, though not always of the nature desired, so that retrofitting with surrogate data is often necessary. A few of the recent advances in data and tools to analyze them are discussed below.

2.3.1 More powerful computers and associated technology

Moore's Law has generally held true over the past two decades, resulting in a phenomenal sustained rate of development and an increase in capacity for processing pixels. For example, Riitters *et al.* (2000, 2002) and Riitters and Wickham (2003) have assessed global patterns at 1 km and conterminous United States patterns at 30 m resolution.

2.3.2 Small data recorder technology

Small data loggers now can be attached to a plethora of devices to allow long-term data recording of various environmental attributes. For example, our group has used them to determine soil and air temperatures, by landscape position, during and in the months following prescribed fires (Iverson and Hutchinson 2002, Iverson *et al.* 2004b). With these sensors, researchers can spatially locate temperature profiles, map and analyze them across landscapes, and animate the actual fire behavior through time (e.g., see animation found at http://www.fs.fed.us/ne/delaware/4153/ffs/zaleski_burn.html). These devices are being used in more diverse and creative ways to acquire data long term and in spatially disparate locations – both very important for landscape ecology.

2.3.3 GPS/GIS on hand-held computers

With the same trend of shrinking computer components comes advances in hand-held computers. GPS and GIS software now can be used effectively on palm-sized units, thus permitting much wider access of the technology to field biologists and others who otherwise have plenty of field equipment to lug around.

2.3.4 Software in image analysis, spatial statistics, modeling, pattern metrics, GIS

Software development has been rapid and diverse as well. The field of data mining and machine learning has been rapidly developing (e.g., Breiman 1996, 2001). Spatial statistics have been a real focus for some time (e.g., Cliff and Ord 1981, Burrough 1987, Legendre and Fortin 1989, Cressie 1991). Analytical techniques not only have been developed by and for landscape ecologists (e.g., McGarigal, this volume), but also borrowed and modified from other fields.

2.3.5 Remote sensing sensors

Many sensors are orbiting that weren't a decade ago (Table 2.1). The pixel sizes have gotten considerably smaller – now often 1 m or less – and the amount of data being transmitted daily to Earth is measured in petabytes (10^{15} bytes). Several countries are involved in developing the sensors and operating the

TABLE 2.1. *Current satellites*

Satellite	Country	Launch	Best resolution (m)	Type[a]
Landsat 7	US	1999	15	Mid-Opt
EO-1	US	2000	10	Mid-Opt
SPOT-2	France	1990	10	Mid-Opt
SPOT-4	France	1998	10	Mid-Opt
SPOT-5	France	2002	2.5	Mid-Opt
CBERS-1	China/Brazil	1999	20	Mid-Opt
Ziyuan-ZY-2A	China	2000	9	Mid-Opt
Ziyuan-ZY-2B	China	2002	3	Mid-Opt
KOMPSAT-1	Korea	1999	6.6	Mid-Opt
Proba (hyperspectral)	ESA	2001	18	Mid-Opt
UoSat 12	Singapore	1999	10	Mid-Opt
DMC AlSat-1	Algeria	2002	32	Mid-Opt
ASTER	US	1999	15	Mid-Opt
ERS-2	ESA	1995	30	Mid-Rad
ENVISAT	ESA	2002	30	Mid-Rad
RadarSat 1	Canada	1995	8.5	Mid-Rad
AVHRR	US	1978	1000	Low-Opt
MODIS	US	1999	250	Low-Opt
Landsat MSS	US	1972	79	Low-Opt
IKONOS	US	1999	1	High-Opt
QuickBird-2	US	2001	0.6	High-Opt
EROS A1	Israel	2000	1.8	High-Opt
IRS TESS	India	2001	1	High-Opt
Helios-1A	France	1995	1	High-Opt
Helios-1B	France	1999	1	High-Opt

[a] Low-Mid-High = resolution class, Opt = optical sensor, Rad = Radar sensor
From: William Stoney, Mitretek Systems.

satellites. Many of the highest-resolution satellites are commercial, while the coarser sensors are publicly operated and more utilized in research. For example, the MODIS sensor, with pixels 250–1000 m, is providing numerous maps, including estimated gross primary productivity, leaf area index, and fraction of photosynthetic active radiation on a regular basis (e.g., Running 2002, Zhang *et al.* 2003).

2.3.6 Data clearing houses

Data is becoming more freely available as government and multi-government agencies and nongovernment organizations are anxious to have

TABLE 2.2. *Example data clearing houses available on the Internet*

Site	Common type of data	Organization
www.natureserve.org	Biodiversity	NatureServe
edc.usgs.gov	Environmental	US Geological Survey
www.wcmc.org.uk/cis/	Biodiversity	World Conservation Monitoring Centre
www.grid.unep.ch	General	United Nations Environmental Program
gcmd.gsfc.nasa.gov/	Remotely Sensed	US National Atmospheric Space Administration
www.gbif.org	Biodiversity	Global Biodiversity Information Facility
fsgeodata.fs.fed.us	Forests, Environment	US Forest Service
geodata.gov	General	US Government
www.nbii.gov/	Biological Resources	National Biological Information Infrastructure

all data, but especially publicly supported data, available to maximize efficiency (as long as national or environmental security is not compromised). As such, several data clearing houses are on the internet to allow free download of data. Some examples are listed in Table 2.2.

2.4 What we will have soon

We should expect the recent trends in data acquisition will continue. National security reviews since September 11, 2001, have reduced the scope of high-resolution data available on the Internet, but otherwise, the trends will lead to better hardware, software, and data availability. Remote data collection via sensors attached to data recorders on the ground or satellites in the sky will pave the way for almost unimaginable sources of data on our landscapes over the long term. As an example of likely near-future data sources, William Stoney (personal communication) has compiled a list of more than 50 mid- and high-resolution sensors targeted for activation within the next few years (Table 2.3).

2.5 Issues of data quality

A better understanding of spatial data quality requires abandonment of two basic beliefs that have been the bane of GIS since the beginning: (1) information shown on maps and captured into a GIS is always correct and essentially void of uncertainty, and (2) numerical information from computers is

TABLE 2.3. *Sensors targeted for activation by 2007*[a]

Satellite	Country	Sponsor[a]	Best resolution (m)	Type[b]
OrbView 3	US	Com	1	High-Opt
IKONUS.X	US	Com	0.5	High-Opt
QuickBird.X	US	Com	0.5	High-Opt
OrbView X	US	Com	0.5	High-Opt
EROS B1	Israel	Com	0.5	High-Opt
EROS B2	Israel	Com	0.5	High-Opt
EROS B3	Israel	Com	0.5	High-Opt
EROS B4	Israel	Com	0.5	High-Opt
IRS Cartosat 2	India	Gov	1	High-Opt
Pleiades-1	France	Gov	0.7	High-Opt
Pleiades-2	France	Gov	0.7	High-Opt
Helios-2A	France	Mil	<1	High-Opt
Helios-2B	France	Mil	<1	High-Opt
IGS-01	Japan	Mil	1	High-Opt
IGS-02	Japan	Mil	1	High-Opt
Resurs DK-1	Russia	Gov	0.4	High-Opt
Resurs DK-2	Russia	Gov	0.4	High-Opt
Resurs DK-3	Russia	Gov	0.4	High-Opt
KOMPSAT-2	Korea	Gov	1	High-Opt
TerraSAR X	Germany	Gov	1	High-Rad
TerraSAR L	Germany	Gov	1	High-Rad
SAR-Lupo-1	Germany	Mil	1	High-Rad
SAR-Lupo-2	Germany	Mil	1	High-Rad
COSMO-Skymed-1	Italy	Gov	1	High-Rad
COSMO-Skymed-2	Italy	Gov	1	High-Rad
COSMO-Skymed-3	Italy	Gov	1	High-Rad
COSMO-Skymed-4	Italy	Gov	1	High-Rad
IGS-R1	Japan	Mil	1 to 3	High-Rad
IGS-R2	Japan	Mil	1 to 3	High-Rad
Resurs DK-2	Russia	Gov	1	High-Rad
Resurs DK-3	Russia	Gov	1	High-Rad
LCDM-A	US	Com	7.5	Mid-Opt
LCDM-B	US	Com	7.5	Mid-Opt
RapidEye-A	Germany	Com	6.5	Mid-Opt
RapidEye-B	Germany	Com	6.5	Mid-Opt
RapidEye-C	Germany	Com	6.5	Mid-Opt
RapidEye-D	Germany	Com	6.5	Mid-Opt
IRS ResourceSat-1	India	Gov	6	Mid-Opt

(*cont.*)

TABLE 2.3. *(cont.)*

Satellite	Country	Sponsor[a]	Best resolution (m)	Type[b]
IRS ResourceSat-2	India	Gov	6	Mid-Opt
CBERS-2	China/Brazil	Gov	20	Mid-Opt
DMC China DMC	China	Gov	4	Mid-Opt
CBERS-3	China/Brazil	Gov	5	Mid-Opt
CBERS-4	China/Brazil	Gov	5	Mid-Opt
RocSat2	Taiwan	Gov	2	Mid-Opt
ALOS	Japan	Gov	2.5	Mid-Opt
DMC NigeriaSat-1	Nigeria	Gov	32	Mid-Opt
DMC ThaiPhat	Thailand	Gov	36	Mid-Opt
DMC BilSat	Turkey	Gov	12	Mid-Opt
DMC UK	UK	Gov	32	Mid-Opt
TopSat	UK	Gov	2.5	Mid-Opt
DMC VinSat-1	Vietnam	Gov	4	Mid-Opt
RadarSat 2	Canada	Gov	3	Mid-Rad
ALOS	Japan	Gov	7	Mid-Rad

[a] Com = Commercial; Gov = Government; Mil = Military
[b] Low-Mid-High = resolution class, Opt = optical sensor, Rad = Radar sensor
From William Stoney, Mitretek Systems.

somehow endowed with inherent authority (Shi *et al.* 2002b). This blind acceptance of GIS data is its Achilles heel and could undermine the entire technology (Goodchild 1998). Maps present a clarified, simplified view of a world that is actually complex and confusing. People prefer this simplified view, and explicit attention to uncertainty muddles this perspective. Nonetheless, it is especially important to pay attention to uncertainty in spatial data because of its importance in decision-making. Decision-makers usually don't want to know about uncertainty and they view GIS as an attractive simplicity. However, courts are likely to hold that a GIS user should make reasonable efforts to deal with uncertainty and they are likely to take a dim view of regulations or decisions based on GIS data in which issues of uncertainty have been ignored. Therefore, avoiding the issue of uncertainty will hurt the credibility of the profession.

2.5.1 Sources of uncertainty in spatial data

Burrough and McDonnell (1998) state that most GIS procedures assume that: (1) source data are uniform, (2) digitizing is infallible, (3) map overlay is simply intersecting boundaries and reconnecting line network,

(4) boundaries can be sharply defined and drawn, (5) all algorithms operate in a fully deterministic way, and (6) class intervals defined for "natural" reasons are the best for all mapped attributes. Of course, these implications are rarely true in landscape ecological studies and must be rectified. Much of the uncertainty can be traced to the original capture and automation of the data. It is especially important to have consistency and proper error checking when a large corporate database is being developed and will be used by many people (Lund and Thomas 1995). Here are some sources of spatial data error (adapted from Stine and Hunsaker 2001):

- *Geometric error*: When data are collected on the Earth (a sphere), and transferred to a map (a plane), there are inaccuracies in projecting the locations.
- *Attribute error*: In measuring an attribute at a point, there may be bias or error in the measuring tool or the person taking the measurement. This error is especially prominent in categorical variables when interpreting class membership (e.g., which vegetation type is this?).
- *Locational/boundary uncertainty*: Positions, through a variety of reasons (e.g., digitizing errors, GPS errors, field-to-map errors), are commonly misrepresented relative to their true positions. These positional errors can matter to a greater or lesser extent depending on the attribute of interest. For example, Lewis and Hutchinson (2000) assessed the impact of positional error for estimates of slope angle and elevation, and found that small positional errors among three maps led to a highly correlated estimate for elevation ($R^2 = 0.95$–0.98) but not for slope ($R^2 = 0.18$–0.32). Boundaries of many ecological units are fuzzy, so their depictions as lines of no width in a GIS will carry significant uncertainty.
- *Physical changes of attributes over time*: Nearly all biologically relevant variables on landscapes change over time, yet most GIS systems hold data for only one time stamp. Landscape ecologists can learn much from stacking two or more time stamps and analyzing the changes, but caution is required to make sure that errors in each of the time stamps are properly handled (Walsh *et al.* 1987).
- *Data compatibility*: When combining data of different qualities, there are new errors introduced. For example, in the case of combining two dates of satellite data, if one is Landsat MSS and the other is Landsat TM, the differences in spatial and spectral resolution can be important. Or, if slope aspect is derived from two digital elevation models of different spatial resolution, the estimates are likely to be quite different.
- *Errors in interpreting and manipulating data*: This error source includes several data processes that can introduce error, such as class aggregations,

changing map projections, and conversions between raster and vector data.

- *Inability to accurately detect attribute of interest*: In many cases, landscape ecologists are not able to measure the variables of interest, but instead use surrogates that hopefully are correlated to the attribute of interest. For example, in the United States, the Heinz Report on the State of the Nation's Ecosystems (Heinz Center 2002) uses 102 indicators on ecosystem status, yet only 32 percent of the indicators have adequate data for assessment. The remainder have to be estimated from surrogates or not assessed at all.

2.5.2 Considering uncertainty in landscape models

Landscape ecologists frequently are using models to better understand the system in which they work and to evaluate the influence of an altered condition (Sklar and Hunsaker 2001). Several ecological phenomena have spatially explicit characteristics important to consider in the models, including environmental gradients, migration, immigration and emigration, metapopulation dynamics, competition, fire behavior, and biogeochemical cycling (Stine and Hunsaker 2001). These models are subject to several sources of uncertainty, most of which can be traced to uncertainty in data collection, data processing, model structure, human intervention, and natural variability (Li and Wu 2006). Of these five, only model structure is unique to the development of landscape models. Within model structure, there are five places where error can influence model outputs (Sklar and Hunsaker 2001):

(1) *Inputs* – the scale of simulated events and states should match the scale of events and states of the data used by the model. For example, a habitat model is much different from a global climate model and data inputs should be matched to the questions being asked.

(2) *Initial conditions* – every model requires identification of the conditions at a particular point in time and across the entire modeled space as the model starts. Often these conditions must be estimated, with associated uncertainty, through interpolation and interpretation of point data.

(3) *Forcing functions* – these are the inputs needed to move the simulation to the next time step. Inputs collected temporally, such as temperature or precipitation, often are used as drivers in the simulation, and errors in these functions can significantly affect the outputs. The most significant uncertainty results from missing data so that, in our example, widely dispersed meteorological stations may present problems, especially for fine-scale simulations.

(4) *Calibration parameters* – the mathematical structure that defines rules, processes, statistical relationships, or state change in the model, to maximize observed and simulated resemblance. These relationships will not be perfectly modeled, so errors are imbedded in the outputs.
(5) *Verification components* – observational and simulated data again are compared, but the observational data have not been used in the model development. Again, errors are similar to those of calibration except that time increases uncertainty and error is cumulative with time in model outputs.

In general, there is a tradeoff in that the more complex the model, the more potential for learning and prediction, but the less accurate (more uncertain) the outputs. There are four categories of dynamic landscape models (Sklar and Hunsaker 2001):

(1) *Transitional probability models* – not mechanistic, but rely on maps from two or more dates to calculate historical trends, which then can be applied forward.
(2) *Gradient models* – for modeling landscapes with obvious upstream and downstream components.
(3) *Process-based mosaic models* – distributes pattern across the landscape using site-specific biogeochemical mechanisms to control energy and material flows.
(4) *Individual-based models* – focus on behavior rules for an individual or an assemblage of individuals as a function of spatial constraints and opportunities.

Sklar and Hunsaker (2001) also discuss the causes of uncertainty in each of these model types.

2.6 Needs in data acquisition and quality

In the pages following, I present 14 topics related to data acquisition and quality which I believe need additional research or effort to advance the credibility and value of the field of landscape ecology and its role in society. There is no particular order to this list. Many of these ideas have been gleaned or modified from other sources, including Mower and Congalton (2000), Hunsaker *et al.* (2001), Wu and Hobbs (2002), and Shi *et al.* (2002a).

2.6.1 Strengthen capacity to collect ground information

World citizens, public officials, and academic institutions need to devise a way to populate the world with many "ologists carrying GPS units, preferably in the context of long-term landscape monitoring programs, and to organize the acquired data into hierarchical, GIS databases. Basic biological data on organisms and communities is still needed! Natural historians have been diminishing in number, and when coupled with increasing information and spatial location requirements in this spatially aware age, ground-observed information is lacking for accurate spatial processing. These kinds of data are critical for research on biological invasions, conservation planning and monitoring, sustainability, cause and effects of stressors, change analysis, systems and complexity analysis, and model development and validation.

Associated with the collection of basic biological data is the nearly equally important role of automating, managing, and serving up the data. There are several organizations doing this to various degrees. The state of Illinois, USA, began automating and distributing information on distributions, ecology, taxonomy, and wildlife and human interactions for more than 3200 plant species in the 1980s (Iverson *et al.* 1997b, Iverson and Prasad 1998a, Iverson and Prasad 1999). The National Biological Information Infrastructure, the World Conservation Monitoring Centre, NatureServe, and the Global Biodiversity Information Facility are four other servers of this kind of information (Table 2.2).

2.6.2 Develop key indicators of status and health of landscapes

To efficiently monitor status and trends, scientists need to identify key indicators within various landscape types that can be readily monitored over large areas with reasonable costs. As mentioned previously, the "The State of the Nation's Ecosystems" report for the United States presented 102 indicators, but only a third have adequate data and many require research on effective monitoring strategies (Heinz Center 2002). Other indicators could be developed, especially those that may be more regional in character. Many other projects have been conducted to assess status and trends of particular locations or landscape components (e.g., Iverson *et al.* 1989b, Illinois Department of Energy and Natural Resources 1994, Mac *et al.* 1998, Shifley and Sullivan 2002), but all have been limited in scope and reliability by the selected indicators and the available data.

2.6.3 Design efficient, multi-tiered sampling designs

It remains a challenge to sample across large regions in a way that provides information at multiple scales, while permitting the inference of the effects of spatial heterogeneity. For instance, many soil and vegetation variables have substantial spatial variability within a few meters, yet we are trying

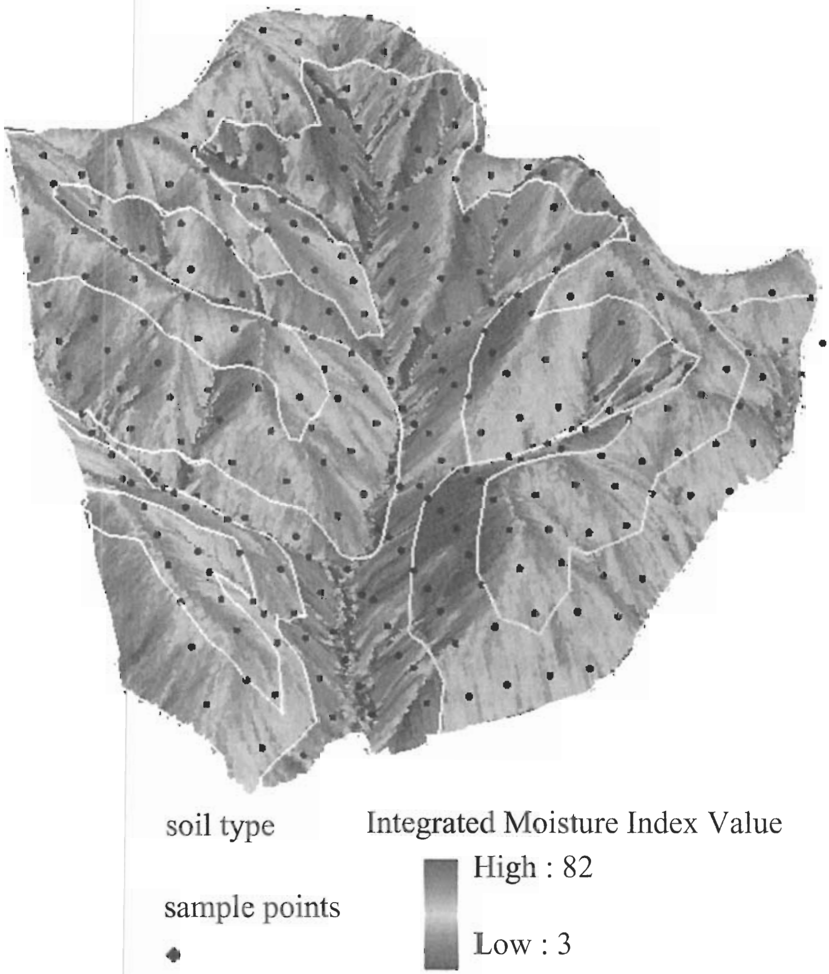

FIGURE 2.1
Integrated Moisture Index at 2 m resolution, vegetation sample points at 50 m spacing, and soil polygons at about 100 m resolution for a study site in southern Ohio, USA

to make repeatable, large-area assessments. For example, in Ohio a map of 1 m digital elevation modeled for integrated moisture index shows very high local variability (Fig. 2.1), also reported for soil nitrogen availability (Boerner *et al.* 2000). What is the best way to extend and use this type of information across large areas? Innovative sampling methods are needed, using creative combinations of current and new methods in field sampling, experimentation, remote sensing, statistics, and modeling. Projects like BIGFOOT (Burrows *et al.* 2002) combine flux towers with multiple ground and remote sensing instruments to extend detailed information across large areas. Earlier, forest plot data, Landsat

TM, and AVHRR data were used to map forest cover (Iverson *et al.* 1989a,b, 1994) and productivity (Cook *et al.* 1987, 1989). In these and similar projects, however, more research is needed to uncover methods to clearly distinguish "noise" from the fine-scale heterogeneity that can be attributed to measured phenomena.

2.6.4 Design and implement global landscape monitoring programs

Society needs to implement global monitoring programs now. The tools are currently available to begin. The incentives are high to do assessments of status and change, for these ecological processes and functions are critical to life itself! Initially, this program should be largely driven by (nearly) free satellite data, which are multiple in scale and with a time series of data. For example, we now have Landsat MSS data back to 1972, Landsat TM back to ~1982, AVHRR back to ~1978, and SPOT (*Satellite Pour l' Observation de la Terre*) back to 1986. These programs have sufficient data to establish such a program. As discussed previously, the satellite data streams are available now and are increasing dramatically. Today's hardware and software can handle the huge data sizes. The program should be interdisciplinary and be able to integrate the most appropriate methodologies from each discipline. And it should permit adaptive management so that as the science, the indicators, and public opinion evolve, so can the questions being asked of the program. In the United States, the proposed National Ecological Observatory Network (NEON) (Holsinger *et al.* 2003) is working toward this goal, but similar efforts are needed globally.

2.6.5 Develop efficient tools for strategic ground sampling

As stated in Section 2.6.1 above, there are not enough natural historians collecting data on species, etc., on the ground in a spatially organized way. There will never be enough. Therefore, strategic methods must be derived to get the most "bang for the buck" when it comes to sampling species. We need GIS tools which will better target ground sampling, so field crews will have a higher probability of encountering the species of interest. In this way, places rich in threatened and endangered species or invasive species, or biologically rich communities, could be modeled and then visited for verification. As an example, Iverson and Prasad (1998a) used a GIS model for 102 Illinois counties to predict possible plant species richness that had been under-sampled based on the richness in the well-sampled counties. Similar efforts and strategies have been presented by Palmer *et al.* (2002) and Ferrier *et al.* (2002).

2.6.6 Develop methods to share sensitive ground-specific information

Sometimes ground-specific information, or at least the specific locations of that information, is sensitive in that it cannot be freely shared without restriction. This restriction may be deemed necessary to protect national security, threatened or endangered organisms, or the rights of private landowners. It would be great if the information could be shared for research and monitoring purposes, but not cause legal or other problems. We need research into methods that might allow the ecological information to be gleaned without legal constraints. For example, the US Forest Service Forest Inventory and Analysis (FIA) program, by law, cannot release coordinates of their plots which number in the hundred thousands. This restriction greatly limits research on plant-environment studies. FIA is incorporating a "fuzz and swap" technique to fuzz locations slightly and to swap attributes with the nearest similar neighbor, which would at least allow summarizing to coarse-level polygons (Charles Scott, US Forest Service, personal communication). Somewhat related is the issue of credit versus data sharing for researchers. Too often researchers are reluctant to submit their data for meta- or regional analysis because they have not yet fully published on the data, even though the data were collected with public funds. Conversely in many instances, the collector(s) of the ground data is forgotten by the researchers doing the regional analyses.

2.6.7 Enhance and categorize methods to interpolate/extrapolate point-level data across landscapes

Because it is not possible, or at least practical, to completely sample any landscape attribute that can't be sensed remotely via satellite or aerial photograph, there always will be a need for interpolation methods to map attributes spatially across landscapes from point-sampled data. Attributes needing to be mapped include species or community distributions, fuels, basal areas, soil properties, climatic data, and air quality. There are several methods available, and the list is growing. What tools to use has been a question for a long time and has been reviewed extensively elsewhere (e.g., Lam 1983, Franklin 1995, Guisan and Zimmerman 2000, Lehmann *et al.* 2002, Leibhold 2002). Some of the methods, along with citations to case studies, follow (in no particular order):

- Regressions (general linear models, general additive models, etc.) (James and McCulloch 1990, Iverson *et al.* 1997b, Austin 1998, Franklin 1998, Cawsey *et al.* 2002, Lehmann *et al.* 2002, Moisen and Frescino 2002). Regression includes a wide array of models in which predictor variables, often in a stepwise fashion, are selected which explain variation in the response variable or variables. Often models are built by fitting lines to data that minimize the sum of the squared residuals.

- Kriging (e.g., universal, indicator) (Rossi *et al.* 1992, Leibhold *et al.* 1993, 1994, Hershey 1996, Riemann-Hershey and Reese 1999). These methods are theoretically based in multiple linear regression and use semi-variograms to describe spatial structure in data, as well as predict values across nonsampled areas. Implicit is the notion that samples close together in time and/or space will be more similar than those that are farther apart. These methods preserve the spatial structure and variability inherent in the sample data but do not work well with ancillary data and usually predict a univariate response.
- Splines (e.g., thin plate splines) (Mitasova and Hofierka 1993, Hutchinson 1995, Mitasova *et al.* 1996, Price *et al.* 2000, Hofierka *et al.* 2002). These interpolation functions include tension and smoothing parameters so that a digital elevation model (DEM), for example, can be viewed as a thin plate built at a higher resolution from points, and the tension adjusted to minimize overshoots and artificial pits in the resulting DEM.
- Classification and regression trees (CART) (Breiman *et al.* 1984, Franklin 1998, Iverson and Prasad 1998b, Moisen and Frescino 2002). The model is fit using recursive partitioning rules, where data are split into left and right branches according to rules defined by the predictor variables. At the terminal node, the predicted value (regression trees) or class (classification trees) is estimated.
- Multivariate adaptive regression splines (MARS) (Freidman 1991, DeVeaux *et al.* 1993, Prasad and Iverson 2000, Moisen and Frescino 2002). MARS is related to classification and regression trees in that it is a flexible nonparametric regression method that generalizes the piecewise constant functions of CART to continuous functions by fitting (multivariate) splines.
- Computer-intensive data mining and prediction techniques (Breiman 1996, 2001, Iverson *et al.* 2004a). These advanced machine-learning techniques use multiple CART trees in determining the best predictive models, including measures of variable importance within the models. Bagging and random forests are techniques that use a bootstrap approach to identify variable importance and produce averaged models, sometimes with as many as 1000 CART trees involved.
- Inverse distance weighted methods (ESRI 1993, Price *et al.* 2000). These methods apply a simple linearly weighted combination of a set of sample points, with the weight being a function of inverse distance.

- Most-similar-neighbor methods (Moeur and Stage 1995, Ohmann and Gregory 2002). These methods provide site-specific data for nonsampled areas by choosing the most similar parcel from a set of sampled parcels to act as its surrogate. Ohmann and Gregory (2002) combined most-similar-neighbor methods with direct-gradient analysis (canonical-correspondence analysis) to produce reasonably accurate vegetation maps.
- Artificial neural networks (Ripley 1994, Cairns 2001, Moisen and Frescino 2002). With neural networks, accurate models can be built for prediction when the underlying relationships between predictor and response are unknown; the response is a transformation of a weighted combination of the predictor variables. The many coefficients and intercepts are "learned" via an optimization method. It is more of a "black box", however, in that the influences of specific variables are difficult to discern.

As a corollary to the above methods, to spread point-level information out across the landscape is also the critical, and often more important, task of determining where boundaries lie among the patches on the landscape. This is also an area of active research (e.g., Fortin 1994, Fortin and Drapeau 1995, Lopez-Blanco and Villers-Ruiz 1995, Wang and Hall 1996, Bernert *et al.* 1997, Fortin *et al.* 2000).

2.6.8 Develop techniques to best acquire and archive information on landscape history

When we learn about the history of a landscape, we can learn more about what is currently making the landscape tick. Ecological legacies are extremely important in most locations, and they can last for many decades, even centuries. Fires, clearing, grazing, wind storms, floods, hurricanes, volcanoes, and land-use changes are example legacies that can have long-lasting effects (Wallin *et al.* 1994, Foster *et al.* 1998, August *et al.* 2002, Turner *et al.* 2003).

Landscape history is also important to document so that, especially with respect to trends in deforestation, historical trends in one part of the world can be used to aid in predicting future trends in another part of the world. Then, if need be, actions can be taken to prevent history from repeating itself. One of the most distasteful, and sadly often repeated, patterns on the planet is when native peoples are "displaced" by colonists from another place (Diamond 1999). Often but not necessarily related is the subsequent rapid conversion of its lands as the new colonists settle. Deforestation patterns in the temperate

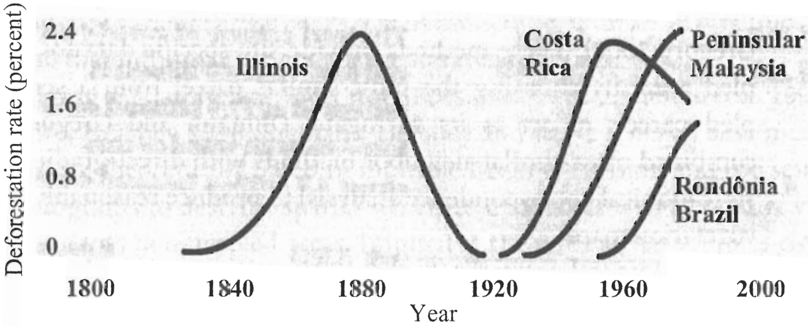

FIGURE 2.2
Rates (percent) of deforestation in Illinois, USA, followed by Costa Rica, Peninsular Malaysia, and Rondônia, Brazil (from Iverson *et al.* 1991). A rate of 2 percent a year would decimate a forest in less than a generation. History does indeed repeat itself

forests of Illinois, USA, for example, have more recently been repeated, and still continue, in the tropical forests of Costa Rica, Malaysia, and Brazil (Fig. 2.2).

We now have many years of data for data mining and evaluation of land-use histories, yet these data are being under-utilized. We have air photos since the early 1930s, Landsat MSS since ~1972, Landsat TM since ~1982, AVHRR since ~1978, and SPOT since 1986. We have sampling station data (e.g., forest plots, water quality sampling, bird census, etc.) over a very long history, but the oldest data often are not digital. Those data that are digital are yielding tremendous value, for example with respect to the breeding bird survey data, continuous since the mid 1960s (James *et al.* 1996, Sauer *et al.* 2001, Rodriguez 2002, Matthews *et al.* 2004).

Unfortunately, we also have decades of data perishing in old file cabinets and storehouses as retirements and budget issues prevent a wealth of data from being captured digitally. This is a tragic loss in these days where the evaluation of long-term trends is such a critical component of many of today's environmental issues.

2.6.9 Determine appropriate methods to merge and analyze data acquired at different scales

Often the significant biological events (e.g., rare occurrences, invasions of exotics) are happening at very fine scales, but we can't collect data everywhere at that scale. We therefore need to have suitable methods for scaling up and scaling down to obtain appropriate estimates for the scale of interest (e.g., Wiens 1989, Rastetter *et al.* 1992, Ehleringer and Field 1993, Gardner *et al.* 2001, Schneider 2001, Cushman and McGarigal 2002). This is an area of active research and discussed in separate chapters by Ludwig and Wu.

As an example from our research laboratory, we now have 1 m elevation data from LIDAR (Light detection and ranging sensor) and can calculate an integrated moisture index (Iverson *et al.* 1997a) on those data, but we cannot obtain that resolution for soils or vegetation attributes. How do we correctly merge and analyze such data so that we best understand the relationships between long-term moisture and soil and vegetation characteristics (Fig. 2.1)?

2.6.10 Efficiently handle increasing volumes of data, with minimal user pre-processing

There are petabytes of data streaming back to Earth each day. We need additional research to facilitate the pre-processing and screening of these data so landscape researchers can readily obtain and process the filtered data with less data volume and less up-front cost. As an example, the MODIS (Moderate-resolution imaging spectroradiometer) sensor has a science team that has been developing algorithms for automatic calculation for several vegetation-related metrics so that each user doesn't have to do it (Running 2002, Heinsch *et al.* 2003, Zhang *et al.* 2003).

2.6.11 New GIS technologies needed

There are at least four areas where the development of GIS technology must proceed to enhance the work of landscape ecologists and the subsequent accountability of that work. We should appeal to vendors and developers to proceed with these developments. First, we need a temporal GIS, one that allows better analysis of changes through time. Second, we need more development in three-dimensional GIS, for better analysis of volumetric and mass-flow data. Third, we need the development of an "uncertain GIS," one that allows the quantifying, display, and analysis of various forms of uncertainty (e.g., Duckham and McCreadie 2002). Fourth, we need the development of automatic metadata tracking within the GIS, so that a complete history and documentation of data generation and manipulation, including error tracking, occurs without human intervention (Beard 2001, Gan and Shi 2002).

2.6.12 Develop and test theory and methods of uncertainty analysis of landscape data

Though several books have been produced on this topic (e.g., Goodchild and Gopal 1989, Mowrer *et al.* 1996, Mowrer and Congalton 2000, Hunsaker *et al.* 2001, Shi *et al.* 2002a), there is still a lot of research needed so that every landscape ecologist and GIS user can understand the critical nature spatial uncertainty plays in their projects. Some areas needing further development include graphical visualization of uncertainty (e.g., Buttenfield 2001, Drecki 2002), error metrics calculation (e.g., Arbia *et al.* 1998), and the simulation of specific uncertainties for testing analytical procedures.

2.6.13 Devise methods so error can be evaluated and broken down into its various components (error budget)

Here I emphasize the need to be able to determine *where* the error lies in any GIS analysis – which form of error mentioned earlier in this chapter is most problematic, and therefore how might that error be trimmed? Or as an example, how can error associated with imagery classification be separated from error associated with a simulation model? Or, how does error propagate and accumulate in various spatial analyses such as overlay and buffer operations? Much of the difficulty associated with this research need is a fundamental flaw in the GIS systems that have been developed and accepted over the past 30 years. Goodchild (2002) discussed the need for a measurement-based GIS, rather than the nearly universal coordinate-based GIS, which cannot properly deal with error. Measurement-based GIS could retain details of measurements, such that error analysis is possible, and corrections to positions can be appropriately propagated through the database.

2.6.14 Devise methods to assess the effects of varying data quality and grain size on the outputs of landscape pattern analysis, model simulations, and resultant decisions

The quality of data and metadata will determine landscape ecologists' ability and effectiveness of detecting patterns and relating them to processes, and consequently affect research results, practical recommendations, and final decisions. Though some work has been done on the sensitivity of various landscape metrics from varying data quality and grain size (e.g., Wickham and Riitters 1995, Wickham *et al.* 1997, Hargis *et al.* 1998), this is an area needing more research. With respect to grain size, we need to determine with more certainty how the following processes affect uncertainty: aggregation, interpolation, transformation, and re-measurement. For many GIS applications, it is not possible to compare the outputs to an independently derived "truth"; in these cases, it is best to conduct a sensitivity analysis based on randomization of the data (Hunsaker *et al.* 2001). For example, it may be possible to use Monte Carlo simulations to determine if a decision becomes unstable because of poor data quality (Phillips and Marks 1996). Decision-support networks are needed that support error analysis and the spatial characterization of uncertainty (Eastman 2001).

2.7 Policy issues related to data acquisition and quality

In addition to the 14 research-focused issues, there are a few issues which are based primarily in policy, and so are mentioned briefly here. These issues are only presented as idea seeds, with much more effort needed to make them proposals.

First, policy-makers need to get behind the research issues to help provide the finances and exposure to make them happen. Otherwise there is no way that well-supported, globally represented, long-term monitoring programs, as an example, will come into being.

Second, mechanisms are needed to enable agencies and countries to easily cooperate, so that the best data sets possible can be derived and analyzed thoroughly and without perceived or real country-level bias.

Third, rigorous support within the policy arena is needed for adequate education and training so that the science can develop credibly in the most helpful ways for societal benefit. Finally, the public, the decision-makers, and the researchers, need to become aware of GIS/map accuracy issues and the subsequent validity of any information they use (Spear *et al.* 1996, Cornelis and Brunet 2002). For information to be used and useful in the policy arena, and not itself be the subject of debate, it must be policy relevant, technically credible, and politically legitimate (O'Malley *et al.* 2003).

2.8 Conclusions

Remote data acquisition is becoming much easier and consistent, though information obtained on the ground is still critically important, costly to acquire, and generally not achievable by remote sensing. We need to learn how to best use these data resources to monitor and manage Earth's resources. Data quality is still a major stumbling block for researchers and decision-makers, and a current critical research topic.

References

Anderson, J. R., E. E. Hardy, and J. T. Roach. 1976. *A land-use classification system for use with remote-sensor data. Circular* 671. Reston, VA: United States Geological Survey.

Anderson, R. C. 1970. Prairies in the prairie state. *Transactions of the Illinois State Academy of Science* **63**, 214–21.

Arbia, G., D. Griffith, and R. Haining. 1998. Error propagation modelling in raster GIS: overlay operations. *International Journal of Geographical Information Science* **12**, 145–67.

August, P., L.R. Iverson, and J. Nugranad. 2002. Human conversion of terrestrial landscapes. Pages 198–224 in K. Gutzwiller, (ed.). *Applying Landscape Ecology in Biological Conservation*. New York: Springer-Verlag.

Austin, M.P. 1998. An ecological perspective on biodiversity investigations: examples from Australian eucalypt forests. *Annals of the Missouri Botanical Garden* **85**, 2–17.

Beard, K. 2001. Roles of meta-information in uncertainty management. Pages 363–78 in C.T. Hunsaker, M.F. Goodchild, M.A. Friedl, and T.J. Case (eds.). *Spatial Uncertainty in Ecology*. New York: Springer-Verlag.

Bernert, J.A., J.M. Eilers, T.J. Sullivan, K.E. Freemark, and C. Ribic. 1997. A quantitative method for delineating regions: an example for the western Corn Belt plains ecoregion of the USA. *Environmental Management* **21**, 405–20.

Boerner, R.E.J., S.J. Morris, E.K. Sutherland, and T.F. Hutchinson. 2000. Spatial variability in soil nitrogen dynamics after prescribed burning in Ohio mixed-oak forests. *Landscape Ecology* **15**, 425–39.

Breiman, L. 1996. Bagging predictors. *Machine Learning* **24**, 123–40.

Breiman, L. 2001. Random forests. *Machine Learning* **45**, 5–32.

Breiman, L., J. Freidman, R. Olshen, and C. Stone. 1984. *Classification and regression trees*. Belmont, CA: Wadsworth.

Burrough, P.A. 1987. Spatial aspects of ecological data. Pages 213–57 in R.H.G. Jongman, C.J.F. ter Braak, and D.F.R. Jongeren (eds.). *Data Analysis in Community and Landscape Ecology*. Wageningen: Pudoc.

Burrough, P.A. and R.A. McDonnell. 1998. *Principles of Geographical Information Systems*. Oxford: Oxford University Press.

Burrows, S.N., S.T. Gower, M.K. Clayton, *et al.* 2002. Application of geostatistics to characterize leaf area index (LAI) from flux tower to landscape scales using a cyclic sampling design. *Ecosystems* **5**, 667–79.

Buttenfield, B.P. 2001. Mapping ecological uncertainty. Pages 115–32 in C.T. Hunsaker, M.F. Goodchild, M.A. Friedl, and T.J. Case (eds.). *Spatial Uncertainty in Ecology*. New York: Springer-Verlag.

Cairns, D.M. 2001. A comparison of methods for predicting vegetation type. *Plant Ecology* **156**, 3–18.

Cawsey, E.M., M.P. Austin, and B.L. Baker. 2002. Regional vegetation mapping in Australia: a case study in the practical use of statistical modelling. *Biodiversity and Conservation* **11**, 2239–74.

Cliff, A.D. and J.K. Ord. 1981. *Spatial Processes: Models and Applications*. London: Pion.

Cook, E.A., L.R. Iverson, and R.L. Graham (eds.). 1987. *The Relationship of Forest Productivity to Landsat Thematic Mapper Data and Supplemental Terrain Information*. Sioux Falls, SD: American Society for Photogrammetry and Remote Sensing.

Cook, E.A., L.R. Iverson, and R.L. Graham. 1989. Estimating forest productivity with thematic mapper and biogeographical data. *Remote Sensing of Environment* **28**, 131–41.

Cornelis, B. and S. Brunet. 2002. A policy-maker point of view on uncertainties in spatial decisions. Pages 168–85 in W. Shi, P.F. Fisher, and M.F. Goodchild (eds.). *Spatial Data Quality*. New York: Taylor & Francis.

Costanza, R., F.H. Sklar, and M.L. White. 1990. Modeling coastal landscape dynamics. *BioScience* **40**, 91–107.

Cressie, N. 1991. *Statistics for Spatial Data*. New York: John Wiley & Sons Inc.

Cushman, S.A. and K. McGarigal. 2002. Hierarchical, multi-scale decomposition of species-environment relationships. *Landscape Ecology* **17**, 637–46.

DeVeaux, R.D., D.C. Psichogios, and L.H. Ungar. 1993. A comparison of two nonparametric estimation schemes: MARS and neural networks. *Computations in Chemical Engineering* **8**, 819–37.

Diamond, J. 1999. *Guns, Germs, and Steel: The Fates of Human Societies*. New York: W. W. Norton & Co.

Donovan, M.L., D.L. Rabe, and C.E. Olson. 1987. Use of geographic information systems to develop habitat suitability models. *Wildlife Society Bulletin* **15**, 574–9.

Drecki, I. 2002. Visualisation of uncertainty in geographical data. Pages 140–59 in W. Shi, P.F. Fisher, and M.F. Goodchild (eds.). *Spatial Data Quality*. New York: Taylor & Francis.

Duckham, M. and J. E. McCreadie. 2002. Error-aware GIS development. Pages 62–75 in W. Shi, P.F. Fisher, and M.F. Goodchild (eds.). *Spatial Data Quality*. New York: Taylor & Francis.

Eastman, R. 2001. Uncertainty management in GIS: decision support tools for effective use of spatial data resources. Pages 379–90 in C.T. Hunsaker, M.F. Goodchild, M.A. Friedl, and T.J. Case (eds.). *Spatial Uncertainty in Ecology*. New York: Springer-Verlag.

Ehleringer, J.R. and C.B. Field. 1993. *Scaling Processes between Leaf and Landscape Levels*. San Diego: Academic Press.

ESRI (Environmental Systems Research Institute). 1993. *Arc/Info GRID Command Reference*. Redlands, CA: Environmental Systems Research Institute.

Ferrier, S., M. Drielsma, G. Manion, and G. Watson. 2002. Extended statistical approaches to modelling spatial pattern in biodiversity in northeast New South Wales. II. Community-level modelling. *Biodiversity and Conservation* **11**, 2309–38.

Fortin, M.-J. 1994. Edge detection algorithms for two-dimensional ecological data. *Ecology* **75**, 956–65.

Fortin, M.-J. and P. Drapeau. 1995. Delineation of ecological boundaries: comparison of approaches and significance tests. *Oikos* **72**, 120–31.

Fortin, M.-J., R.J. Olson, S. Ferson, *et al.* 2000. Issues related to the detection of boundaries. *Landscape Ecology* **15**, 453–66.

Foster, D.R., D.H. Knight, and J.F. Franklin. 1998. Landscape patterns and legacies resulting from large, infrequent forest disturbances. *Ecosystems* **1**, 497–510.

Franklin, J. 1995. Predictive vegetation mapping: geographic modelling of biospatial patterns in relation to environmental gradients. *Progress in Physical Geography* **19**, 494–519.

Franklin, J. 1998. Predicting the distribution of shrub species in southern California from climate and terrain-derived variables. *Journal of Vegetation Science* **9**, 733–48.

Freidman, J.H. 1991. Multivariate adaptive regression splines. *Annals of Statistics* **19**, 1–141.

Gan, E. and W. Shi. 2002. Error metadata management system. Pages 251–66 in W. Shi, P.F. Fisher, and M.F. Goodchild (eds.). *Spatial Data Quality*. New York: Taylor & Francis.

Gardner, R.H., W.M. Kemp, V.S. Kennedy, and J.E. Petersen. 2001. *Scaling Relations in Experimental Ecology*. New York: Columbia University Press.

Gardner, R.H., B.T. Milne, M.G. Turner, and R.V. O'Neill. 1987. Neutral models for the analysis of broad-scale landscape pattern. *Landscape Ecology* **1**, 19–28.

Goodchild, M.F. 1998. Uncertainty: the Achilles heel of GIS? *Geo Info Systems* **1998** (November), 50–2.

Goodchild, M.F. 2002. Measurement-based GIS. Pages 5–17 in W. Shi, P.F. Fisher, and M.F. Goodchild (eds.). *Spatial Data Quality*. New York: Taylor & Francis.

Goodchild, M.F. and S. Gopal. 1989. *Accuracy of Spatial Databases*. Bristol, PA: Taylor & Francis.

Guisan, A. and N. E. Zimmermann. 2000. Predictive habitat distribution models in ecology. *Ecological Modelling* **135**, 147–86.

Hargis, C.D., J.A. Bissonette, and J.L. David. 1998. The behavior of landscape metrics commonly used in the study of habitat fragmentation. *Landscape Ecology* **13**, 167–86.

Heinsch, F.A., M. Reeves, C.F. Bowker, *et al.* 2003. *User's Guide, GPP and NPP (MOD17A2/A3) Products, NASA MODIS Land Algorithm*. Bozeman, MT: Montana State University.

Heinz Center for Science, Economics and the Environment. 2002. *The State of the Nation's Ecosystems*. Cambridge, UK: Cambridge University Press.

Hershey, R.R. 1996. Understanding the spatial distribution of tree species in Pennsylvania. Pages 73–82 in H.T. Mowrer, R.L. Czaplewski, and R.H. Hamre (eds.). *Spatial Accuracy Assessment in Natural Resources and Environmental Sciences*. General Technical Report RM-GTR-277, Fort Collins, CO: Rocky Mountain Forest and Range Experiment Station, USDA Forest Service.

Hofierka, J., J. Parajka, M. Mitasova, and L. Mitas. 2002. Multivariate interpolation of precipitation using regularized spline with tension. *Transactions in GIS* **6**, 135–50.

Holsinger, K.E. and IBRCS Working Group. 2003. IBRCS White Paper. *Rationale, Blueprint, and Expectations for the National Ecological Observatory Network*. Washington, DC: American Institute of Biological Sciences.

Hopkins, L.D. 1977. Methods for generating land suitability maps: a comparative evaluation. *AIP Journal* **43**, 386–400.

Hunsaker, C.T., M.F. Goodchild, M.A. Friedl, and T.J. Case. 2001. *Spatial Uncertainty in Ecology*. New York: Springer-Verlag.

Hutchinson, M.F. 1995. Interpolating mean rainfall using thin plate smoothing splines. *International Journal of Geographical Information Systems* **9**, 385–403.

Illinois Department of Energy and Natural Resources. 1994. *The Changing Illinois Environment: Critical Resources*. Volume 3. Technical Report. ILENR/RE-EA-94/05. Springfield, IL: Illinois Department of Energy and Natural Resources.

Iverson, L.R. 1988. Land-use changes in Illinois, USA: the influence of landscape attributes on current and historic use. *Landscape Ecology* **2**, 45–61.

Iverson, L.R., E.A. Cook, and R.L. Graham. 1989a. A technique for extrapolating and validating forest cover data across large regions: calibrating AVHRR data with TM. *International Journal of Remote Sensing* **10**, 1805–12.

Iverson, L.R., E.A. Cook, and R.L. Graham. 1994. Regional forest cover estimation via remote sensing: the calibration center concept. *Landscape Ecology* **9**, 159–74.

Iverson, L.R., M.E. Dale, C.T. Scott, and A. Prasad. 1997a. A GIS-derived integrated moisture index to predict forest composition and productivity in Ohio forests. *Landscape Ecology* **12**, 331–48.

Iverson, L.R. and T.F. Hutchinson. 2002. Soil temperature and moisture fluctuations during and after prescribed fire in mixed-oak forests, USA. *Natural Areas Journal* **22**, 296–304.

Iverson, L.R., R.L. Oliver, D.P. Tucker, *et al.* 1989b. *Forest Resources of Illinois: An Atlas and Analysis of Spatial and Temporal Trends*. Champaign, IL: Illinois Natural History Survey Special Publication 11.

Iverson, L.R. and L.G. Perry. 1985. Integration of biological pieces in the siting puzzle. Pages 99–131 in *The Siting Puzzle: Piecing Together Economic Development and Environmental Quality*. Proceedings of the 13th Annual ENR Conference. Springfield, IL: Illinois Department of Energy and Natural Resources.

Iverson, L.R. and A. Prasad. 1998a. Estimating regional plant biodiversity with GIS modeling. *Diversity and Distributions* **4**, 49–61.

Iverson, L.R. and A.M. Prasad. 1998b. Predicting abundance of 80 tree species following climate change in the eastern United States. *Ecological Monographs* **68**, 465–85.

Iverson, L.R. and A.M. Prasad. 1999. The Illinois Plant Information Network (database). www.fs.fed.us/ne/delaware/ilpin/ilpin.html.

Iverson, L.R., A. Prasad, and D.M. Ketzner. 1997b. A summary of the Illinois flora based on the Illinois Plant Information Network. *Transactions of the Illinois State Academy of Science* **90**, 41–64.

Iverson, L.R., A.M. Prasad, and A. Liaw. 2004a. New machine learning tools for predictive vegetation mapping after climate change: bagging and random forest perform better than regression tree analysis. Pages 317–20 in R. Smithers (ed.). Proceedings, Cirencester, UK: UK-International Association for Landscape Ecology.

Iverson, L.R. and P.G. Risser. 1987. Analyzing long-term changes in vegetation with geographic information system and remotely sensed data. *Advances in Space Research* **7**, 183–94.

Iverson, L.R., D.A. Yaussy, J. Rebbeck, *et al.* 2004b. A data recording method to monitor the spatial and temporal distribution of fire behavior from prescribed fires. *International Journal of Wildland Fire* **13**, 1–12.

James, F.C. and C.E. McCulloch. 1990. Multivariate analysis in ecology and systematics: panacea or Pandora's box? *Annual Review of Ecology and Systematics* **21**, 129–66.

James, F.C., C.E. McCulloch, and D.A. Wiedenfield. 1996. New approaches to the analysis of population trends in land birds. *Ecology* **77**, 13–27.

Klopatek, J.M., R.J. Olson, C.J. Emerson, and J.L. Jones. 1979. Land-use conflicts with natural vegetation in the United States. *Environmental Conservation* **6**, 191–200.

Krummel, J.R., R.H. Gardner, G. Sugihara, R.V. O'Neill, and P.R. Coleman. 1987. Landscape patterns in a disturbed environment. *Oikos* **48**, 321–4.

Lam, N.S. 1983. Spatial interpolation methods: a review. *The American Cartographer* **10**, 129–49.

Legendre, P. and M.-J. Fortin. 1989. Spatial pattern and ecological analysis. *Vegetatio* **80**, 107–38.

Lehmann, A., J.M. Overton, and M.P. Austin. 2002. Regression models for spatial prediction: their role for biodiversity and conservation. *Biodiversity and Conservation* **11**, 2085–92.

Leibhold, A.M. 2002. Integrating the statistical analysis of spatial data in ecology. *Ecography* **25**, 553–7.

Leibhold, A.M., R.E. Rossi, and W.P. Kemp. 1993. Integrating the statistical analysis of spatial data in ecology. *Annual Review of Entomology* **38**, 303–27.

Lewis, A. and M.F. Hutchinson. 2000. From data accuracy to data quality: using spatial statistics to predict the implications of spatial error in point data. Pages 17–35 in H.T. Mowrer and R.G. Congalton (eds.). *Quantifying Spatial Uncertainty in Natural Resources*. Chelsea, MI: Ann Arbor Press.

Li, H. and J. Wu. 2006. Uncertainty analysis in ecological studies: an overview. Pages 45–66 in J. Wu, B. Jones, B. Li, and O.L. Loucks (eds.). *Scaling and Uncertainty Analysis in Ecology: Methods and Applications*. Dordrecht, the Netherlands: Springer.

Lopez-Blanco, J., and L. Villers-Ruiz. 1995. Delineating boundaries of environmental units for land management using a geomorphological approach and GIS: a study in Baja California, Mexico. *Remote Sensing and Environment* **53**, 109–17.

Lund, H.G. and C.E. Thomas. 1995. *A Primer on Evaluation and Use of Natural Resource Information for Corporate Data Bases*. US Department of Agriculture Forest Service, General Technical Report WO-62. Washington, DC: Washington Office.

Mac, M.J., P.A. Opler, C.E. Puckett Haecker, and P.D. Doran. 1998. *Status and Trends of the Nation's Biological Resources*. Reston, VA: US Geological Survey.

Matthews, S.N., R.J. O'Connor, L.R. Iverson, and A.M. Prasad. 2004. *Atlas of Current and Climate Change Distributions of Common Birds of the Eastern United States. General Technical Report NE-318.* Newtown Square, PA: USDA Forest Service, Northeastern Research Station.

Mitasova, H. and J. Hofierka. 1993. Interpolation by regularized spline with tension: II. Application to terrain modeling and surface geometry analysis. *Mathematical Geology* **25**, 657–69.

Mitasova, H., J. Hofierka, M. Zlocha, and L.R. Iverson. 1996. Modeling topographic potential for erosion and deposition using GIS. *International Journal of Geographical Information Systems* **10**, 629–41.

Moeur, M. and A.R. Stage. 1995. Most similar neighbor: an improved sampling inference procedure for natural resource planning. *Forest Science* **41**, 337–59.

Moisen, G.G. and T. Frescino. 2002. Comparing five modelling techniques for predicting forest characteristics. *Ecological Modelling* **157**, 209–25.

Moore, G.E. 1965. Cramming more components into integrated circuits. *Electronics* **38**, 1–4.

Mowrer, H.T. and R.G. Congalton. 2000. *Quantifying Spatial Uncertainty in Natural Resources: Theory and Applications for GIS and Remote Sensing*. Chelsea, MI: Ann Arbor Press.

Mowrer, H.T., R.L. Czaplewski, R.H. Hamre, and Tech coords. 1996. *Spatial Accuracy Assessment in Natural Resources and Environmental Sciences: Second International Symposium*. General Technical Report RM-GTR-277. Fort Collins, CO: USDA Forest Service, Rocky Mountain Forest and Range Experiment Station.

O'Malley, R., K. Cavender-Bares, and W.C. Clark. 2003. Providing "better" data: not as simple as it might seem. *Environmental Conservation* **45**, 8–18.

O'Neill, R.V., J.R. Krummel, R.H. Gardner, *et al.* 1988. Indices of landscape pattern. *Landscape Ecology* **1**, 153–62.

Ohmann, J.L. and M.J. Gregory. 2002. Predictive mapping of forest composition and structure with direct gradient analysis and nearest-neighbor imputation in coastal Oregon, USA. *Canadian Journal of Forest Research* **32**, 725–41.

Olson, R.J., C.J. Emerson, and M.K. Nungesser. 1980. *Geoecology: A County-Level Environmental Data Base for the Conterminous United States*. Publication No. 1537. Oak Ridge, TN: Oak Ridge National Laboratory Environmental Sciences Division.

Palmer, M.W., P.G. Earls, B.W. Hoagland, P.S. White, and T. Wohlgemuth. 2002. Quantitative tools for perfecting species lists. *Environmetrics* **13**, 121–37.

Phillips, D.L. and D.G. Marks. 1996. Spatial uncertainty analysis: propagation of interpolation errors in spatially distributed models. *Ecological Modeling* **9**, 213–30.

Prasad, A.M. and L.R. Iverson. 2000. Predictive vegetation mapping using a custom built model-chooser: comparison of regression tree analysis and multivariate adaptive regression splines. In Proceedings CD-ROM. 4th International Conference on Integrating GIS and Environmental Modeling: Problems, Prospects and Research Needs. Banff, Alberta, Canada (http://www.colorado.edu/research/cires/banff/upload/159/index.html).

Price, D.T., D.W. McKenney, I.A. Nalder, M.F. Hutchinson, and J.L. Kesteven. 2000. A comparison of two statistical methods for spatial interpolation of Canadian monthly mean climate data. *Agricultural and Forest Meteorology* **101**, 81–94.

Rastetter, E.B., A.W. King, B.J. Cosby, *et al.* 1992. Aggregating fine-scale ecological knowledge to model coarser-scale attributes of ecosystems. *Ecological Applications* **2**, 55–70.

Riemann-Hershey, R. and G. Reese. 1999. *Creating a "First-cut" Species Distribution Map for Large Areas from Forest Inventory Data*. General Technical Report NE-256. Radnor, PA: Northeastern Research Station, USDA Forest Service.

Riitters, K., J. Wickham, R. O'Neill, B. Jones, and E. Smith. 2000. Global scale patterns of forest fragmentation. *Conservation Ecology* **4**, 3 [online] URL: http://www.consecol.org/Journal/vol4/iss2/art3.

Riitters, K.H. and J.D. Wickham. 2003. How far to the nearest road. *Frontiers in Ecology and the Environment* **1**, 125–9.

Riitters, K.H., J.D. Wickham, R.V. O'Neill, *et al.* 2002. Fragmentation of continental United States forests. *Ecosystems* **5**, 815–22.

Ripley, B.D. 1994. Neural networks and related methods for classification. *Journal of the Royal Statistical Society B* **56**, 409–56.

Risser, P.G. and L.R. Iverson. 1988. Geographic information systems and natural resource issues at the state level. Pages 231–239 in D.B. Botkin, M.E. Caswell, J.E. Estes, and A.A. Orio (eds.). *Our Role in Changing the Global Environment: What We Can Do About Large Scale Environmental Issues*. New York: Academic Press.

Risser, P.G., J.R. Karr, and R.T.T. Forman. 1984. *Landscape Ecology: Directions and Approaches*. Champaign, IL: Illinois Natural History Survey Special Publication Number 2.

Rodriguez, J.P. 2002. Range contraction in declining North American bird populations. *Ecological Applications* **1**, 238–48.

Rossi, R.E., J.L. Dungan, and L.R. Beck. 1994. Kriging in the shadows: geostatistical interpolation for remote sensing. *Remote Sensing of the Environment* **49**, 32–40.

Rossi, R.E., D.J. Mulla, A.G. Journel, and E.H. Franz. 1992. Geostatistical tools for modeling and interpreting ecological spatial dependence. *Ecological Monographs* **62**, 719–35.

Running, S.W. 2002. New satellite technologies enhance study of terrestrial biosphere. *EOS, Transactions, American Geophysical Union* **83**, 458–60.

Sauer, J.R., J.E. Hines, and J. Fallon. 2001. The North American breeding bird survey, results and analysis 1966–2000. Version 2001.2. Laurel, MD: USGS Patuxent Wildlife Research Center. (http://www.mbr.nbs.gov/bbs/htm96/trn626/all.html).

Schneider, D.C. 2001. The rise of the concept of scale in ecology. *Bioscience* **51**, 545–54.

Shi, W., P.F. Fisher, and M.F. Goodchild. 2002a. *Spatial Data Quality*. New York: Taylor & Francis.

Shi, W., M.F. Goodchild, and P.F. Fisher. 2002b. Epilog: a prospective on spatial data quality. Pages 304–9 in W. Shi, P.F. Fisher, and M.F. Goodchild (eds.). *Spatial Data Quality*. New York: Taylor & Francis.

Shifley, S.R. and N.H. Sullivan. 2002. *The Status of Timber Resources in the North Central United States*. General Technical Report NC-228. St. Paul, MN: North Central Research Station, USDA Forest Service.

Sklar, F.H. and C.T. Hunsaker. 2001. The use and uncertainties of spatial data for landscape models: an overview with examples from the Florida Everglades. Pages 15–46 in C.T. Hunsaker, M.F. Goodchild, M.A. Friedl, and T.J. Case (eds.). *Spatial Uncertainty in Ecology*. New York: Springer-Verlag.

Spanner, M.A., A.M. Strahler, and J.E. Estes. 1983. Soil loss prediction in a geographic information system format. Pages 89–102 in *Seventeenth International Symposium on Remote Sensing of Environment*. Ann Arbor, MI: Environmental Research Institute of Michigan.

Spear, M., J. Hall, and R. Wadsworth. 1996. Communication of uncertainty in spatial data to policy makers. Pages 199–207 in H.T. Mowrer, R.L. Czaplewski, and R.H. Hamre (eds.). *Spatial Accuracy Assessment in Natural Resources and Environmental Sciences*. General Technical Report RM-GTR-277, Fort Collins, CO: USDA Forest Service, Rocky Mountain Forest and Range Experiment Station.

Stine, P.A. and C.T. Hunsaker. 2001. An introduction to uncertainty issues for spatial data used in ecological applications. Pages 91–107 in C.T. Hunsaker, M.F. Goodchild, M.A. Friedl, and T.J. Case (eds.). *Spatial Uncertainty in Ecology*. New York: Springer-Verlag.

Turner, M.G. 1988. A spatial simulation model of land use changes in a piedmont county in Georgia. *Applied Mathematics and Computation* **27**, 39–51.

Turner, M.G., R. Costanza, and F.H. Sklar. 1989. Methods to evaluate the performance of spatial simulation models. *Ecological Modelling* **48**, 1–18.

Turner, M.G., W.H. Romme, and D.B. Tinker. 2003. Surprises and lessons from the 1988 Yellowstone fires. *Frontiers in Ecology and the Environment* **1**, 351–8.

Wallin, D.O., F.J. Swanson, and B. Marks. 1994. Landscape pattern response to changes in pattern-generation rules: land-use legacies in forestry. *Ecological Applications* **4**, 569–80.

Walsh, S.J., D.R. Lightfoot, and D.R. Butler. 1987. Recognition and assessment of error in geographic information systems. *Photogrammetric Engineering and Remote Sensing* **53**, 1423–30.

Wang, F. and G.B. Hall. 1996. Fuzzy representation of geographical boundaries in GIS. *International Journal of Geographical Information Systems* **10**, 573–90.

Wickham, J.D., R.V. O'Neill, K.H. Riitters, T.G. Wade, and K.B. Jones. 1997. Sensitivity of selected landscape pattern metrics to misclassification and differences in land cover composition. *Photogrammetric Engineering and Remote Sensing* **63**, 397–402.

Wickham, J.D. and K.H. Riitters. 1995. Sensitivity of landscape metrics to pixel size. *International Journal of Remote Sensing* **16**, 3585–94.
Wiens, J.A. 1989. Spatial scaling in ecology. *Functional Ecology* **3**, 385–97.
Wu, J. and R. Hobbs. 2002. Key issues and research priorities in landscape ecology: an idiosyncratic synthesis. *Landscape Ecology* **17**, 355–65.
Zhang, X., M.A. Friedl, C.B. Schaaf, *et al.* 2003. Monitoring vegetation phenology using MODIS. *Remote Sensing of the Environment* **84**, 471–5.