Landsat's Role in Ecological Applications of Remote Sensing

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Remote sensing, geographic information systems, and modeling have combined to produce a virtual explosion of growth in ecological investigations and applications that are explicitly spatial and temporal. Of all remotely sensed data, those acquired by Landsat sensors have played the most pivotal role in spatial and temporal scaling. Modern terrestrial ecology relies on remote sensing for modeling biogeochemical cycles and for characterizing land cover, vegetation biophysical attributes, forest structure, and fragmentation in relation to biodiversity. Given the more than 30-year record of Landsat data, mapping land and vegetation cover change and using the derived surfaces in ecological models is becoming commonplace. In this article, we summarize this large body of work, highlighting the unique role of Landsat.

Keywords: remote sensing, Landsat, spectral vegetation indices, vegetation mapping, change detection

The discipline of ecology has undergone tremendous growth and diversification over the past century. These advances were driven by a variety of sociological, political, environmental, and technological developments that fostered new theory as well as new applications. Public concern over the state of the environment, which had been increasing over the decades leading up to the 1960s, led to landmark sociopolitical action. The Clean Air Act of 1963, later amended in 1970 and 1990, was perhaps the most important initial legislative action. Another major legislative event was the Endangered Species Act of 1973. Emerging environmentalism led to the establishment of an annual event known as Earth Day, first celebrated in 1970 and continuing today.

With regard to technology, the foundations were laid in the 1960s and 1970s for what would become widely known as geographic information systems (GIS). Electronic computing, revolutionized with the development of microprocessors in the early 1970s, ushered computing into the realm of environmental research, which ultimately enabled GIS to pervade environmental modeling.

On the theoretical forefront at the time was the development and appreciation of what by the 1990s was to become perhaps the dominant concept in ecology: scale. With respect to advancement in applications of spatial (and to a lesser extent temporal) scaling theory, there has been perhaps no greater catalyst than remote sensing. At the core of developments in remote sensing has been the Landsat program.

Launch of the Sputnik satellite in 1957 ushered in the Space Age. In 1962, John Glenn became the first human to orbit the Earth. During the manned Gemini and Apollo programs from 1965 to 1972, numerous pictures were taken of Earth from space, and a discipline known as remote sensing was born. With the launch of the first Landsat satellite in 1972, scientists could suddenly view tangible human impacts on the whole Earth system on a regular basis. By necessity, field measurements and experiments focused (and have continued to focus) mainly on plots with sizes up to several square meters (m^2). Remote sensing enabled scientists to spatially reference their plots to images showing the land-cover and landform context of their data. Because Landsat data were digital, they could be used with other, thematic data sets in cartographic modeling schemes using GIS. This enabled spatially explicit ecological models to expand from local into regional applications.

For regional monitoring applications relying on temporal data sets, Landsat has several advantages. First, with more than 30 years of Earth imaging, it offers the longest-running time series of systematically collected remote sensing data. Second, the grain size (or spatial resolution) of the data facilitates characterization of land cover and cover change associated with the grain of land management. Third, Landsat Thematic Mapper (TM) and the later Enhanced Thematic Mapper Plus (ETM+) acquire spectral measurements in all major portions of the solar electromagnetic spectrum

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(visible, near-infrared [NIR], shortwave-infrared [SWIR]), providing Landsat TM and ETM+ significant advantages over less capable sensor systems. Fourth, in recent years Landsat data have become more affordable, as have the computers needed to process these data, making it possible to acquire and analyze large volumes of observations.

In the remainder of this article we give a brief historical overview of the Landsat program, paying particular attention to the initial vision for the program, the quality of its sensors, its role in the evolution of remote sensing, and its current status. This is followed by a discussion of the importance of Landsat to the development of spectral vegetation indices and to the emergence of the power of SWIR reflectance in ecological applications of remote sensing. We then present a section highlighting various ecological applications of Landsat data, including their integration with ecological models. We finish with a summary of the importance of remote sensing to ecology today, describing how Landsat has been—and will continue to be for the foreseeable future—a key contributor to spatiotemporal scaling in ecology.

Historical overview of the Landsat program

The tradition of taking the high ground to get a better perspective on landscapes and ecosystems is probably as ancient as human curiosity. The technology to support such efforts took a major step forward in the mid-1800s, when cameras were first taken aloft in hot air balloons to better record spatial variations in the land surface. At the end of World War II, scientific understanding and several emergent technologies came together to produce the type of systematic, global land-monitoring observatories that are available today. Landsat was the first spacecraft system deployed to conduct terrestrial monitoring, and it remains the preeminent observatory for monitoring regional land dynamics.

The scientific basis for Landsat originated from the understanding that photosynthetically active vegetation produces a unique solar reflectance spectrum, with low reflectance in visible wavelengths and high reflectance in NIR wavelengths. There are early reports on the use of NIR photography in ecology, but it was only during and shortly after World War II that remote sensing systems began to fully take advantage of the potential for multispectral measurements in terrestrial research.

The unique vegetation reflectance spectrum served as the basis for color-infrared (CIR) photography, which was used for camouflage detection by the military. Such photography also began to be used for high-altitude acquisitions from the US U-2 spy planes, because, by avoiding the shorter-wavelength (blue) visible wavebands, the imagery was less contaminated by haze, giving a clearer view of the land surface from these high altitudes (approximately 18 kilometers [km]). Similar significant success was achieved from space in the Apollo/Gemini program. This imagery proved valuable for land-cover assessments, agricultural surveys, and forest inventories. Thus, the CIR approach was deemed optimal for unmanned, spaceborne imaging systems.

Technical components of the Landsat concept consisted of Earth-orbiting spacecraft, electronic sensors, and electronic computers. All of these components primarily emerged following World War II. The late 1950s found the United States and the Soviet Union in a cold war battle to achieve primacy in these areas. The efforts to orbit television cameras for gathering weather information represented a US success in this direction. By the early 1960s, the US military was beginning to declassify these technologies and encourage government and university scientists to more fully explore their value for civil uses. Research teams at institutions, including the University of Michigan, the University of California–Berkeley, Purdue University, and the US Department of Agriculture (USDA) research laboratory in Weslaco, Texas, began to explore the details of how to exploit the new electronic, multispectral measurements.

By the mid-1960s, the National Aeronautics and Space Administration (NASA), primarily through the Apollo program, had encouraged the US Department of the Interior and USDA to consider the value of a dedicated land observation mission. The head of the US Geological Survey (USGS) at that time, William T. Pecora, took a particular interest in this concept, producing the initial proposal for an Earth Resources Observation Satellite. Ultimately, NASA was given the lead to develop the Earth Resources Technology Satellite (ERTS, later renamed Landsat). The first observatory was launched in 1972. USGS was given the archival responsibility to capture and distribute these data at the new Earth Resources Observation System Data Center in Sioux Falls, South Dakota. From 1972 to date, there have been seven Landsats launched—one launch approximately every 3 years through Landsat 5, which was launched in 1984, followed by two more launches in the 1990s. Landsat 6 was launched approximately 9 years after Landsat 5, in 1993, but failed to achieve orbit. Interestingly, this was the only satellite in the series that did not involve NASA oversight. Landsat 7 was launched in 1999, 6 years after Landsat 6.

When ERTS was under construction, the primary observation instrument was considered the three-band (red, green, NIR) return beam vidicon (RBV) instrument. In simple terms, this was a shuttered television camera that imaged a 185-km by 185-km land area. The assumption was that the radiometry and mapping geometry of this system was the best that could be achieved at the time, at least with electronic systems in which the data were transmitted to the ground. In addition, a proposal to fly a four-band multispectral scanner sensor (MSS), with green, red, and two NIR bands, originated out of the multispectral work being pursued at Michigan, Purdue, Berkley, and elsewhere. The goal of the MSS system was to explore the potential of numerical multispectral imaging, particularly as analyzed by electronic computers. Ultimately, both systems were flown to provide an opportunity to compare them. Shortly after launch, electrical problems with the RBV camera resulted in its being shut down. The MSS system became the sole source of imagery from near the beginning of the mission. Interestingly, comparisons of the early RBV and MSS image pairs demonstrated that the MSS system provided better imagery. The three-band RBV system was flown on Landsat 2 but not used nearly as much as the MSS system. For Landsat 3, the RBV was converted to a panchromatic system at higher spatial resolution (30 m), in an effort to complement the MSS system. Unfortunately, analog transmission of the RBV data made them quite noisy when compared with the digitally transmitted MSS data. The RBV system was discontinued after Landsat 3.

In the early 1970s, NASA researchers were assigned the task of developing a more advanced MSS system, in the view that it would produce considerable advances in land evaluations based on its enhanced performance characteristics. This system, which ultimately became Landsat TM, was deployed on Landsat 4 in association with an MSS system that duplicated the sensor used on Landsats 1, 2, and 3. The TM instrument is similar to the original MSS system in that it is a multispectral scanner. However, the technical capabilities of the TM instrument are a substantial enhancement over those of the MSS. Whereas the MSS instrument had a four-band, six-bit radiometry and a nominal 80-m instantaneous field of view (IFOV, the area viewed on the ground, which was technically 79 m by 56 m), the TM instrument is a seven-spectral-band sensor (one of which is thermal and has a 120-m IFOV) with eight-bit radiometry and a 30-m IFOV. Although the MSS was continued on Landsats 4 and 5, interest quickly shifted to the science and applications of the TM instrument after its first deployment in 1982 on Landsat 4. Landsat 7 introduced ETM+, which included a 15-m IFOV panchromatic band, two radiometric sensitivity ranges, and a 60-m IFOV thermal-infrared band. Also, for Landsat 7, an automatic, systematic acquisition scheme was introduced to ensure that clear scenes for most of the globe were acquired seasonally. With a 16-day return time, this scheme made it possible to obtain clear views of the greater part of the terrestrial surface one or more times per year.

In many ways, the politics and varying management approaches that have surrounded Landsat are as interesting and significant as the scientific and technical accomplishments of the mission. From the beginning, budgetary administrators in Washington have had concerns about NASA (or any other federal agency) taking on major new operational obligations, such as the weather satellites or agricultural surveys. Ultimately, NASA was given approval to pursue the Landsat concept as an "experiment." This justification lasted through Landsats 1, 2, and 3 and the launch of Landsats 4 and 5. In the early 1980s, the White House took initial steps toward commercializing Landsat by moving mission management to the National Oceanic and Atmospheric Administration (NOAA). The Reagan administration sped up the process and called for industry bids. A consortium of Hughes Aircraft Company and RCA Corporation formed the Earth Observation Satellite Company, or EOSAT, and won the bid to commercialize the mission. This was a bumpy road for everyone involved and was brought to an end in 1992, when Congress acted to bring the mission back under direct government management. Landsat 6 was lost on launch shortly thereafter, and a major effort, under the direction of NASA and the Department of Defense (DOD), was undertaken to quickly construct Landsat 7.

During the development of Landsat 7, DOD dropped out of mission management because the instrument the department had planned to add was not funded. By presidential directive, Landsat was turned over to NASA, NOAA, and USGS. NOAA dropped out in 1998, when its requested budget for Landsat was also denied. Today, the mission operations for Landsat 7 (as well as Landsat 5) have been turned over to USGS, with NASA supplying technical support. NASA also undertook development of possible advanced sensor technology designs and orbited the Earth Observer–1 (EO-1) satellite with the Advanced Land Imager and the Hyperion hyperspectral sensor to test these possible future directions for continuation of Landsat beyond Landsat 7.

On the political front, there continues to be considerable pressure, under the 1992 public law and other congressional directives, to identify a mission approach that would involve private industry in the continuation of Landsat. From 2001 to 2003, NASA and USGS pursued a government-industry partnership to provide Landsat continuity, involving the release of a request for proposals in November 2002 for the Landsat Data Continuity Mission (LDCM). However, no satisfactory proposal was received and the LDCM procurement was canceled in late 2003. At the time of this writing, other options for the continuity of data beyond Landsat 7 are under consideration, as required by the 1992 law. It should be noted that in May 2003 the operation of one component of the Landsat 7 ETM+ sensor malfunctioned, resulting in a loss of 20% to 25% of the data in every full scene. Compositing approaches to fill in the gaps in the data are being implemented. For most applications, composited products should meet observation requirements.

The Landsat mission is remarkable in many ways. It is an exceptionally successful outgrowth of the US space program, derived primarily from the effort to place a man on the moon (the Apollo program). It has defined a new way of monitoring Earth's land areas, particularly the condition and seasonal dynamics of the vegetated land cover. It has stimulated much international interest in such observations, both through international ground stations and through the development of similar observatories by countries such as France, Russia, Japan, India, Brazil, and China. The Landsat program has now achieved a record of these measurements for more than 30 years and appears to be headed toward at least another decade of measurements, thus surviving despite the turmoil and chaos of Washington politics. One should expect, when looking back on the 50th anniversary of these measurements, that recognition will be given to the remarkable innovation that was developed in the United States in the mid-20th century and permitted scientists to begin truly monitoring life on Earth.

Landsat and the development of spectral vegetation indices

A few years before the launch of ERTS (i.e., Landsat 1), Birth and McVey (1968) evaluated the color of grass turf using a ratio of NIR (750-nanometer [nm]) to red (650-nm) reflectance, which they called the turf color index. Shortly thereafter, Jordan (1969) used a similar index to relate the quality of light on the forest floor to the leaf area index (LAI). This NIR-red ratio is now commonly referred to as the simple ratio and represents an example of the now-numerous algebraic combinations of multispectral measurements that have come to be known as spectral vegetation indices (SVIs). SVIs have been at the heart of ecological applications of remote sensing, and this section briefly describes their development and Landsat's seminal role in the process.

SVIs were originally applied to satellite remote sensing using the first Landsat MSS system. A precursor to what is now called the normalized difference vegetation index (NDVI, defined as [NIR – red]/[NIR + red], or the difference divided by the sum of reflectances in the red and NIR spectra), was used by Rouse and colleagues (1974) to track what they called the "greenwave effect" over the growing season in grasslands of the Great Plains. Others soon followed with a demonstration that the phenology of various vegetation types could likewise be monitored with an SVI of MSS data, and that SVIs were more sensitive to phenology than were individual spectral bands (e.g., Blair and Baumgardner 1977).

The simple ratio and NDVI represent ratio-based SVIs, using visible and NIR reflectance, that result in a single index. Given their simplicity and use of commonly acquired spectral ranges, these SVIs have been widely applied over time to numerous data sets from a variety of sensors. However, Landsat data were also key to the development of algebraic combinations of spectral bands that result in related sets of SVIs, including those that utilize SWIR bands.

Consideration of the spectral development of crops or open-canopy vegetation over a growing season invariably leads to a consideration of soil spectral properties. One of the original conceptual models for this was the "tasseled cap" (Kauth and Thomas 1976). Recognizing that all four spectral channels of MSS data contain useful information, Kauth and Thomas statistically rotated the full MSS data space into a physically meaningful set of SVIs, the primary ones being brightness and greenness. The key point here is that soil reflectance is variable and that it is desirable to have an SVI that responds to amount of green vegetation irrespective of soil reflectance, which, as demonstrated by Kauth and Thomas, exists as a plane in multidimensional MSS space (at the base of what formed a tasseled cap). This was quickly followed by a simplification of the plane of soils to a conceptual soil line, with new MSS SVIs as spectral measures of the amount of vegetation independent of soil conditions.

With the launch of Landsat 4 and the wide availability of TM data, a new index was added to the tasseled cap to account for new information available from SWIR. In a model dubbed the "TM tasseled cap," a new series of indices—brightness, greenness, and wetness—was derived. Brightness and greenness were reformulated to account for new sensor characteristics, and wetness was designed to contrast the SWIR bands against the visible and NIR bands in an effort to express the water content of soils and other scene components (Crist and Cicone 1984). With the addition of wetness, it was now possible to fully express the tasseled cap model in three spectral dimensions, which together formed the plane of vegetation (brightness and greenness), the plane of soils (brightness and wetness), and the transition zone (wetness and greenness).

Whereas the weighting of the different bands in the original tasseled cap was based on maximizing contrasts for a single Landsat MSS image from Illinois, the TM version was based on three TM scenes, one from the Midwest (Iowa) and two from the South (covering portions of Arkansas, Tennessee, and North Carolina). Although this facilitated a greater exploration of features other than soils and crops, forests remained largely unexplored. This changed with Li and Strahler (1985), who used brightness and greenness to identify the spectral properties of scene components for use in their geometric-optical model of forest structure, and with others who used these SVIs to evaluate forest succession. Cohen and colleagues (1995) examined the three main TM tasseled cap indices, finding that wetness was essentially unaffected by topographic variation in closed conifer stands and thus more powerful than brightness and greenness for predicting forest structural attributes, given that both brightness and greenness responded more to topographic variation than to forest condition.

Landsat-based SVIs also played a large role in the development of methods to detect changes in vegetation condition. Numerous approaches to change detection have been developed, but one of the more conceptually interesting and enduring ones, change vector analysis, was based originally on MSS data (Malila 1980). Change vector analysis describes two-date pixel spectral changes in two dimensions (namely brightness and greenness) in terms of a vector with both direction and magnitude. Later, the conceptual framework was developed to extend change vector analysis into three spectral dimensions to accommodate TM data. Collins and Woodcock (1994) used a different conceptual model to derive change information from TM data, defining both stable and changing components of brightness, greenness, and wetness.

Although it is convenient to give spectral indices names that conjure up visions of what in the Earth system they are sensitive to, it must be kept in mind that spectral data are not that well behaved. As already described, the NDVI responds to both vegetation greenness (or amount) and soil reflectance. Furthermore, brightness and greenness can be more sensitive to topographic variation than to soil or vegetation properties, in which case they can also be very highly correlated to each other.

Emergence of the power of shortwave-infrared reflectance

The previous section indicated that Landsat was the first Earth-observing satellite system to include SWIR channels and to emphasize the importance of the TM tasseled cap index of wetness (which contrasts SWIR against all other spectral channels) in characterizing vegetation environments. At this point, we turn our attention to demonstrating the importance of Landsat TM and its successor, ETM+, to ecological applications of remote sensing, precisely because these systems contain SWIR channels. The importance of SWIR is most widely recognized in the study of forest vegetation.

Horler and Ahern (1986) conducted the first detailed examination of the forestry information content of TM data. They discovered that the SWIR bands contained more information about conifer and hardwood forests of western Ontario and Arkansas than the other bands. Later, it was found that TM SWIR was an important spectral region for estimating forest volume and LAI in conifer forests (e.g., Eklundh et al. 2001). In the greater Yellowstone ecosystem, Jakubauskas (1996) found that SWIR bands explained most of the variance in TM data associated with forest structure. This is similar to the finding that wetness was the most important tasseled cap index for assessing forest structure in western Oregon (Cohen et al. 1995, 2001). Working in Australia, Lymburner and colleagues (2000) reported that SWIR (in addition to visible) bands were the most important TM bands for characterizing variations in specific leaf area across diverse forest and crop types. In the Amazon, Steininger (2000) found the SWIR bands to be the most important TM bands for mapping age and biomass.

Considering the importance of SWIR bands for characterizing forest conditions, it is not unexpected that SWIR bands are also important for assessing forest changes. Using TM simulator data, Williams and Nelson (1986) found that SWIR bands enabled more accurate and detailed characterizations of insect damage in conifer and hardwood forests of North Carolina. Rock and colleagues (1986) likewise found with TM simulator data that a ratio-based SVI that included SWIR was able to detect stress associated with acid rain in Vermont forests. With TM data, the SWIR region has been identified as important for characterizing fire scars, windfall, thinning, and deforestation (e.g., Skole and Tucker 1993, Olsson 1994). Landsat's SWIR capabilities were a central reason that Coppin and colleagues (2001) proposed the system for operational monitoring of the forests of Minnesota.

The importance of SWIR reflectance has also been noted for nonforest applications. Lee and colleagues (1988) reported that the SWIR was the best spectral region for broad soil classification in leaf-off conditions because of its sensitivity to surface texture, organic matter content, and moisture. May and colleagues (1997) found TM to be better than other satellite multispectral data for mapping in a shrub-meadow complex because of its SWIR advantage.

Ecological applications of Landsat data

Landsat data have been translated into useful ecological information for more than 30 years, with both the methods and the applications growing increasingly sophisticated. In this section, we summarize Landsat applications in ecology, highlighting (a) the diversity of the uses of Landsat data to characterize the state and dynamics of ecosystems and (b) the increasing complexity of Landsat's integration with ecological models.

State and temporal dynamics of ecosystems. Ecosystems can be described by their condition (i.e., their state) and by how they are changing (i.e., their temporal dynamics). Since Landsat data became available, they have been regularly used for both purposes across a number of ecosystem types. Numerous studies have evaluated relationships between Landsat data and a number of attributes of vegetation, with some studies using derived maps in environmental applications. Analyses of Landsat have involved both the spectral and the spatial domains of the data, and Landsat data now figure prominently in large-area, operational mapping and monitoring.

Thematic classification. Forest classification (figure 1) has been a popular use of Landsat data for assessing such things as timber volume, wildlife habitat, successional stage, forest fragmentation, invasive species, rare and endangered plant species, biodiversity, and (with multidate data from a single growing season) characteristics of species (e.g., Gluck and Rempel 1996, Poole et al. 1996, Cohen et al. 2001, Dymond et al. 2002, Hansen et al. 2002). In other ecosystem types, classifications derived from Landsat data have been used to model wetland fish productivity, to map bird habitat in mixed cover types, to assess the cover density and productivity of coral reefs, to conduct fire risk assessment in shrublands, and (using multidate, single-season imagery) to map crop types in agricultural regions (e.g., Maselli et al. 1996, Oetter et al. 2001). The usual approach involves identifying spectral properties associated with classes of interest and then assigning class labels to image pixels with those properties.

Biophysics. While spectral-based classification of landscapes into discrete cover types is a prominent application of Landsat data, the use of these data for deriving continuous estimates of vegetation biophysical characteristics has been equally important (figure 2). Inversion of spectral models for isolated vegetation characteristics such as LAI, specific leaf area, biomass, canopy moisture content, and canopy cover has been used across a variety of vegetation types (e.g., Kanemasu et al. 1977, Lymburner et al. 2000, Steininger 2000). In forests, continuous representations of stand age have been derived (Cohen et al. 2001). Model inversions for simultaneous estimation of basic ecosystem component fractions such as soil, vegetation, and shade have been accomplished using mixture modeling approaches (Smith et al. 1990). Continuous surface properties not directly related to vegetation have also been studied with Landsat. Notably, the thermal band of Landsat TM has been used to characterize surface temperature (Holifield et al. 2003), and soil properties such as organic carbon content, phosphorus concentration, and pH have been estimated as continuous variables with Landsat data (e.g., Skidmore et al. 1997).

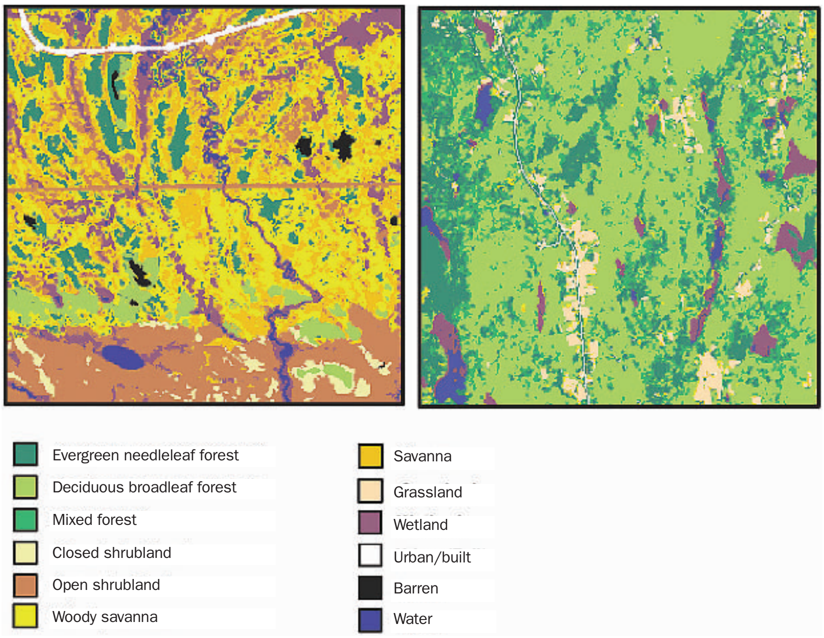

Figure 1. Maps of land and forest cover for 7-kilometer (km) by 7-km sections of boreal forest in northern Canada (left) and mixed deciduous-evergreen forest in eastern Massachusetts (right), derived from Landsat Enhanced Thematic Mapper Plus data.

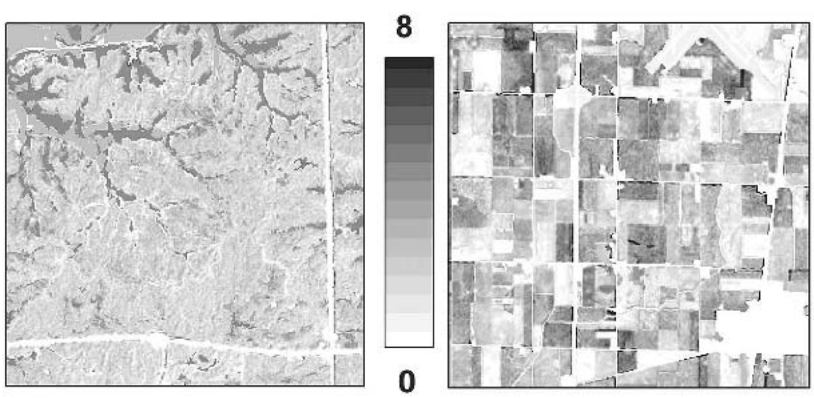

Figure 2. Maps of leaf area index (from 0 to 8 square meters leaf area per square meter land surface) for two 7-kilometer (km) by 7-km sections of grassland in Kansas (left) and agricultural land in Illinois (right), derived from Landsat Enhanced Thematic Mapper Plus data.

Temporal dynamics. Characterizing both seasonal (intra-annual) and interannual dynamics of ecosystems has consistently been an important emphasis in Landsat ecological applications. Although the maximum number of images from any single Landsat sensor has been approximately two per month at any given location, cloud cover and sometimes-complicated acquisition strategies have usually restricted the actual temporal density of images for a given location to something significantly less. Nonetheless, for much of the Earth's surface, this has been sufficient to capture important phenological events. Following the early work of Blair and Baumgardner (1977), who were among the first to demonstrate that Landsat 1 data captured the greening and senescence of hardwood tree canopies, Dymond and colleagues (2002) used intra-annual Landsat data to map hardwood and mixed forests at the species level. For assessing conifer forest structure, Lefsky and colleagues (2001) compared the value of intra-annual TM data with that of single-date TM data, digital airborne data at fine spatial resolution (approximately 1 m), hyperspectral airborne data, and lidar (light detecting and ranging, an active sensor) data. Of the passive sensor data sets compared, intra-annual TM significantly outperformed other data sets.

Assessment of interannual changes in vegetation state using remote sensing is commonly referred to as "change detection." Landsat data have been used for change detection within and across a variety of ecosystem types (figure 3). In forests, there have been successful characterizations of changes associated with clear-cut harvesting, thinning, tree mortality, acid rain, insect damage, windfall, salvage logging, succession, and transition rates among classes (e.g., Rock et al. 1986, Williams and Nelson 1986, Skole and Tucker 1993, Olsson 1994, Collins and Woodcock 1996, Helmer et al. 2000, Cohen et al. 2002).

Spatial patterns. Landsat data have been used to evaluate vegetation spatial patterns in relation to ecology and management. Haralick and colleagues (1973) were among the first to develop textural measures for use with Landsat data. These measures, which are based on neighborhood functions that describe local patterns in image brightness, have been used with Landsat data to assist in classification of urban and linear features, forest cover, sand dunes, and ice-related features (e.g., Gurney and Townshend 1983, Chou et al. 1994). Woodcock and Strahler (1987) developed a local variance function, based on successive coarsening of image spatial resolution, that characterizes spatial pattern as a function of this resolution.

Characterization of landscapes with spatial metrics applied to Landsat data and with maps derived from these applications has been common. Gluck and Rempel (1996) used TM data to characterize patch size, shape, and other metrics for disturbed forests in Canada, finding that clear-cuts were larger and more irregularly shaped than wildfire disturbances. Silbernagel and colleagues (1997) used TM and historic data to assess changing patterns of human settlement and found that human preferences for specific landscape conditions have not changed since prehistoric times.

Semivariograms, graphical descriptions of spatial autocorrelation in spatially explicit data sets, are another important spatial analysis tool used with Landsat data. Such uses include inventory of waste disposal sites, evaluation of the relationship between light transmittance and spectral response of forest canopies, assessment of the effects of autocorrelation on predictive linear regression models that estimate tree cover from spectral response, and mapping of LAI in a boreal forest (e.g., Lathrop and Pierce 1991, McGwire et al. 1993).

Large-area mapping. Maturity of the Landsat program, computing power, and significant knowledge of how to process the data are now developed to the point where operational use of Landsat for mapping large areas is feasible. Lunetta and colleagues (1998) describe the North American Landscape Characterization (NALC) data set, which consists of 1970s, 1980s, and 1990s MSS data, radiometrically and geometrically processed in a consistent manner to prepare them for use in land-cover and cover-change analyses at the continental level. Heilman and colleagues (2002) used the NALC data set to quantify forest fragmentation over the conterminous United States. Vogelmann and colleagues (2001) describe the early-1990s National Land Cover Dataset for the conterminous United States, based on TM data, and discuss its follow-on based on a more recent TM data set (circa 2000). Homer and colleagues (1997) describe the use of TM to map vegetation cover over the state of Utah within the context of the Gap Analysis Program, which has similar objectives and applies similar methods state by state across the United States. McRoberts and colleagues (2002) describe a prototype exercise for eventual use by the US Forest Service in which TM data are the basis for stratifying forest and nonforest at the national level. Cihlar and colleagues (2003) describe a procedure developed in Canada for processing up to hundreds of ETM+ scenes that does not compromise quality of information over that of more localized analyses.

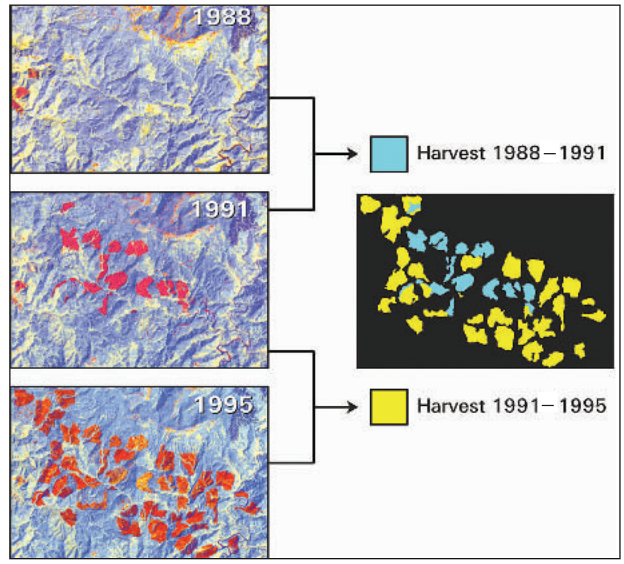

Figure 3. Landsat Thematic Mapper imagery representing three dates for a small (3-kilometer [km] by 5-km) section of forestland in western Oregon and a map of forest harvest activity derived from these data. Images are displayed as tasseled cap indices of brightness, greenness, and wetness (red, green, and blue, respectively).

Integration with ecological models. Soon after ERTS was launched, MSS data were being incorporated into ecological models. Over the past three decades, the number and complexity of models that use Landsat data have grown considerably. Concomitantly, the ways in which Landsat data have been used to initialize and drive ecological models have diversified.

Physiological models. Physiologically based process models are one important class of models that ingest Landsat data. Kanemasu and colleagues (1977) used an LAI derived from MSS data, along with climate data, to drive a simple daily model of evapotranspiration from wheat fields. Kaneko and Hino (1996) estimated surface energy balance over a forested area using parameters derived from TM data. For modeling conifer forest productivity, Nemani and Running (1989) used LAI estimates derived from TM data to test a proposed theoretical equilibrium between LAI and site hydrological properties. With a similar model, Franklin and colleagues (1997) used LAI estimates derived from a combination of TM and GIS to determine how closely modeled and actual LAI were related in mixed forest stands. A light-use-efficiency (LUE) model was used by Goetz and Prince (1996) to derive estimates of boreal forest net primary production (NPP), with intra-annual MSS data used to drive a simple radiative transfer model for calculating light interception by the canopy. As part of a validation of global NPP products derived from the MODIS (Moderate Resolution Imaging Spectroradiometer) sensor, Turner and colleagues (2002) used an LUE model over an agricultural region parameterized with LAI estimates and stratified by land cover type, with both LAI and land-cover estimates derived from ETM+ data. Law and colleagues (forthcoming) integrated ecological modeling; eddy covariance flux tower data; plot data; climate data; and land cover, forest age, and LAI derived from TM and ETM+ to model NPP, gross primary production, and net ecosystem production over a 50-km by 300-km conifer forest area in western Oregon.

Accounting models. Carbon accounting models also utilize Landsat data. Cairns and colleagues (2000) used a relatively simple approach of assigning biomass values to land-cover classes derived from an existing map that was updated with TM data. Comparing this with a similarly derived biomass map for an earlier date, they were able to estimate carbon fluxes over the tropical region of Mexico between 1972 and 1992. Cohen and colleagues (1996) employed a more comprehensive strategy to account for changes in carbon storage over a coniferous forest area in the western United States. The approach relied on a series of integrated models that account not only for temporal changes associated with

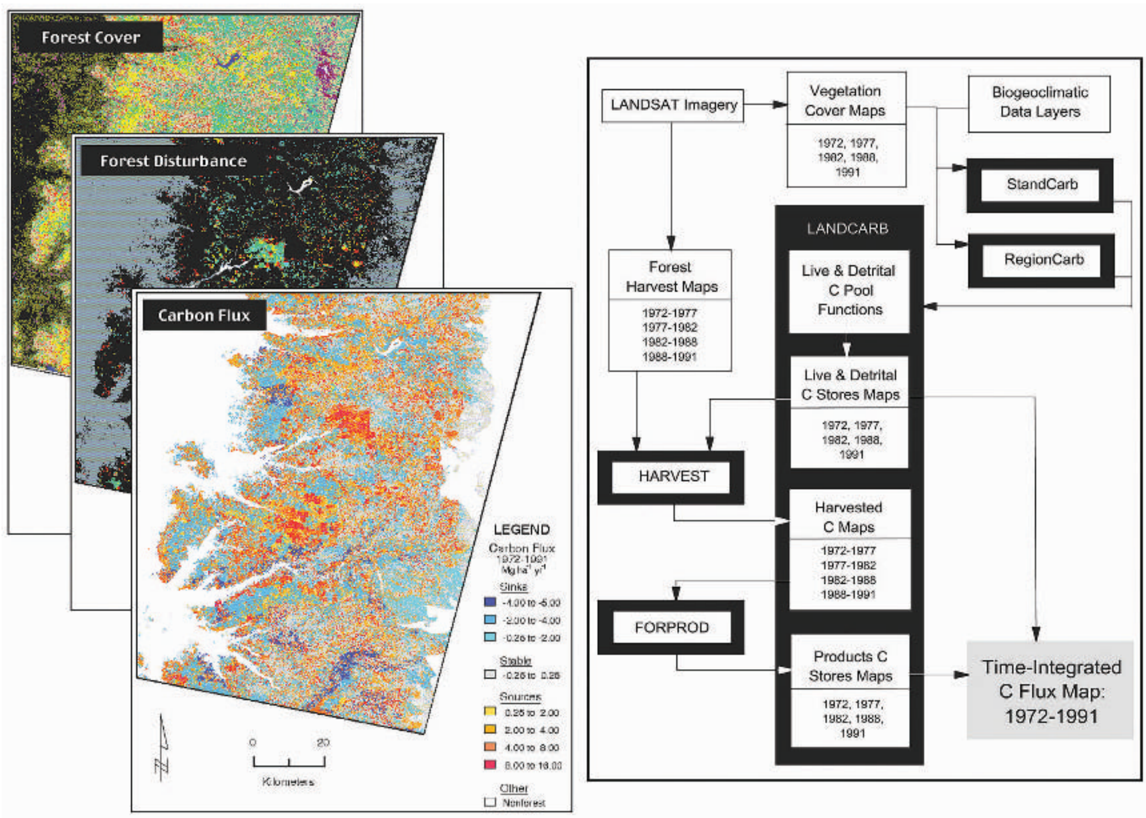

Figure 4. Conceptual model for the development of a time-integrated carbon flux map for approximately 800,000 hectares of forestland in western Oregon. The model uses Landsat imagery for a single date to initialize the forest condition and imagery for multiple dates to detect forest disturbance and succession. These data are used by a series of models to account for carbon dynamics in the forest system and in the forest products sector.

management-driven and geoclimatically driven forest-cover dynamics but also for changes in wood utilization standards and in the forest products processing sector (figure 4). Landsat data were an integral component of this work, both for mapping vegetation cover (Cohen et al. 2001) and for tracking disturbances (Cohen et al. 2002) over broad geographic areas.

Habitat assessments. Studies of wildlife habitat and biodiversity have used Landsat data in a number of ways. The simplest approaches have involved habitat mapping (e.g., in tropical forest, boreal forest, and mixed forest–grassland; Sader et al. 1991, Poole et al. 1996). Mack and colleagues (1997) developed coarse estimates of bird species–area relationships over a woodland area on the basis of TM data. A spatially explicit habitat capability model for the northern spotted owl, developed and tested by McComb and colleagues (2002), relies on Landsat data for habitat characterization.

Socioeconomic studies. Socioeconomic studies, especially those that pertain to land use, increasingly rely on remote sensing for basic information on land cover and land-cover change. However, the grain of the observation (i.e., spatial resolution of imagery) must be small enough to detect the changes. In many cases, (e.g., forest harvesting; Cohen et al. 2002), Landsat and similar sensors are the best choice. In a Landsat-based study of land ownership-induced patterns in a conifer forest landscape of Oregon, Stanfield and colleagues (2002) found that ownership structure explained up to 40% of the variability in forest cover. Helmer (2000) used Landsat data to characterize deforestation in the tropics and then relate observed spatial and temporal land-cover patterns to physical and socioeconomic drivers. Spies and colleagues (2002) describe one of the more complex and highly integrated studies to date that rely on Landsat-derived cover maps to provide basic land-cover and change information (figure 5). That study illustrates the potential for landscape ownership pattern to have a strong influence on ecosystem goods and services at local to regional levels and for integrated research to help visualize the ecological consequences of varying management policies when there are complex and diverse land-management objectives.

Landsat's growing legacy

Over the past several decades, ecological sciences have been greatly influenced by sociopolitical changes. Contemporaneously, technological advances have permitted ecologists to address increasingly complex scientific questions formulated in response to heightened concerns over environmental health and global change. Together with greatly enhanced computing

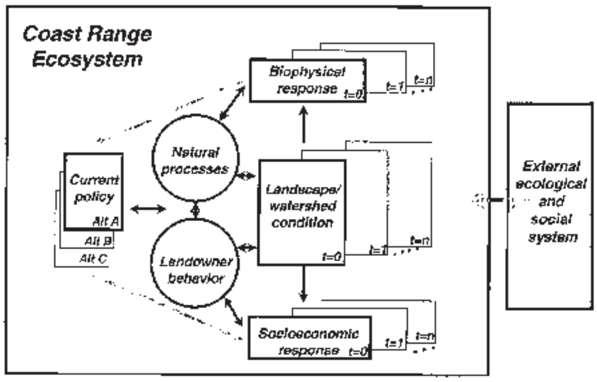

Figure 5. Conceptual model for the Coastal Landscape Analysis and Modeling Study, or CLAMS, linking forest ecology with policy and social processes. Landscape condition at various times (t) is provided by a combination of Landsat-derived maps and forest process simulation models. Future ecological and socioeconomic outcomes are evaluated in response to various hypothetical forest policies. Adapted from Spies and colleagues (2002).

power, maturity in GIS, and advances in cartographic and ecological modeling, remote sensing has been at the center of a spatial (and, to a lesser extent, temporal) explosion in applications of ecology. The ambassador of remote sensing in this context has been the Landsat series of satellites.

Landsat represents the longest-running program for observations of Earth's surface from space. By maintaining a focus on data continuity, incorporating improvements in sensing technology, and adapting to lessons learned from earlier sensors and related applications, the Landsat program has remained vital. Much of the development in spectral vegetation indices, widely used to extract both spatial and temporal ecological information from remotely sensed data, has been facilitated by the broad availability of high-quality Landsat data whose grain size is commensurate with land-use and management activity. The discovery that SWIR reflectance facilitates improved extraction of ecological information over large spatial extents came with Landsat 4 and the TM sensor. Landsat data have been applied across a large array of ecological problems in a variety of environmental settings. Their explicit incorporation into ecological modeling has led to tremendous expansion in modeling sophistication.

The future of Landsat and Landsat-like sensors, and their increasingly integrative role in ecological modeling and applications, is promising. The follow-on to Landsat 7, currently known as the Landsat Data Continuity Mission, should ensure that these high-quality data will be available through at least the end of the next decade, hopefully without a temporal gap in data availability. Development of mapping programs to use large amounts of Landsat data at national and continental scales should foster improvements in ecological modeling and facilitate ecological applications at those scales. We would be remiss, however, if we did not caution that many important ecological properties cannot be remotely sensed with sufficient reliability or with the detail desired, particularly with passive sensors like those on board Landsat satellites. There will remain a strong need for process-based field-oriented studies and for measurements that are best made by other technologies. Integration of Landsat data with data from other, complementary sensors will be the key to improvements in the extraction of information from remotely sensed data.

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References cited

Birth GS, McVey GR. 1968. Measuring the color of growing turf with a reflectance spectrophotometer. Agronomy Journal 60: 640–643.

Blair BO, Baumgardner MF. 1977. Detection of the green and brown wave in hardwood canopy covers using multidate, multispectral data from Landsat-1. Agronomy Journal 69: 808–811.

Cairns M, Haggerty P, Alvarez R, De Jong B, Olmsted I. 2000. Tropical Mexico's recent land-use change: A region's contribution to the global carbon cycle. Ecological Applications 10: 1426–1441.

Chou J, Weger RC, Ligtenberg JM, Kuo KS, Welch R, Breeden P. 1994. Segmentation of polar scenes using multi-spectral texture measures and morphological filtering. International Journal of Remote Sensing 15: 1019–1036.

Cihlar J, Guindon B, Beaubien J, Latifovic R, Peddle D, Wulder M, Fernandes R, Kerr J. 2003. From need to product: A methodology for completing a land cover map of Canada with Landsat data. Canadian Journal of Remote Sensing 29: 171–186.

Cohen WB, Spies T, Fiorella M. 1995. Estimating the age and structure of forests in a multi-ownership landscape of western Oregon, U.S.A. International Journal of Remote Sensing 16: 721–746.

Cohen WB, Harmon ME, Wallin DO, Fiorella M. 1996. Two decades of carbon flux from forests of the Pacific Northwest. BioScience 46: 836–844.

Cohen WB, Maiersperger T, Spies T, Oetter D. 2001. Modelling forest cover attributes as continuous variables in a regional context with Thematic Mapper data. International Journal of Remote Sensing 22: 2279–2310.

Cohen WB, Spies T, Alig R, Oetter D, Maiersperger T, Fiorella M. 2002. Characterizing 23 years (1972–1995) of stand replacement disturbance in western Oregon with Landsat imagery. Ecosystems 5: 122–137.

Collins JB, Woodcock CE. 1994. Change detection using the Gramm-Schmidt transformation applied to mapping forest mortality. Remote Sensing of Environment 50: 267–279.

———. 1996. An assessment of several linear change detection techniques for mapping forest mortality using multitemporal Landsat TM data. Remote Sensing of Environment 56: 66–77.

Coppin P, Nackaerts K, Queen L, Brewer K. 2001. Operational monitoring of green biomass change for forest management. Photogrammetric Engineering and Remote Sensing 67: 603–611.

Crist EP, Cicone RC. 1984. A physically-based transformation of thematic mapper data—the TM tasseled cap. IEEE Transactions on Geoscience and Remote Sensing 22: 256–263.

Dymond C, Mladenoff D, Radeloff V. 2002. Phenological differences in tasseled cap indices improve deciduous forest classification. Remote Sensing of Environment 80: 460–472.

Eklundh L, Harrie L, Kuusk A. 2001. Investigating relationships between Landsat ETM+ sensor data and leaf area index in a boreal conifer forest. Remote Sensing of Environment 78: 239–251.

Franklin S, Lavigne M, Deuling M, Wulder M, Hunt ER Jr. 1997. Estimation of forest leaf area index using remote sensing and GIS data for modelling net primary productivity. International Journal of Remote Sensing 18: 3459–3471.

Gluck M, Rempel R. 1996. Structural characteristics of post-wildfire and clearcut landscapes. Environmental Monitoring and Assessment 39: 435–450.

Goetz S, Prince S. 1996. Remote sensing of net primary production in boreal forest stands. Agriculture and Forest Meteorology 78: 149–179.

Gurney CM, Townshend JR. 1983. The use of contextual information in the classification of remotely sensed data. Photogrammetric Engineering and Remote Sensing 49: 55–64.

Hansen AJ, Rasker R, Maxwell B, Rotella JJ, Johnson JD, Parmenter AW, Langner U, Cohen WB, Lawrence RL, Kraska MPV. 2002. Ecological causes and consequences of demographic change in the New West. BioScience 52: 151–162.

Haralick RM, Shanmugan K, Dinstein I. 1973. Textural features for image classification. IEEE Transactions on Systems, Man, and Cybernetics 3: 610–621.

Heilman GE Jr, Strittholt JR, Slosser NC, Dellasala DA. 2002. Forest fragmentation of the conterminous United States: Assessing forest intactness through road density and spatial characteristics. BioScience 52: 411–422.

Helmer E. 2000. The landscape ecology of tropical secondary forest in montane Costa Rica. Ecosystems 3: 98–114.

Helmer E, Brown S, Cohen WB. 2000. Mapping montane tropical forest successional stage and land use with multi-date Landsat imagery. International Journal of Remote Sensing 21: 2163–2183.

Holifield C, McElroy M, Bryant R, Miura T, Emmerich W. 2003. Temporal and spatial changes in grassland transpiration detected using Landsat TM and ETM+ imagery. Canadian Journal of Remote Sensing 29: 259–270.

Homer CG, Ramsey RD, Edwards TC Jr, Falconer A. 1997. Landscape cover-type modeling using a multi-scene Thematic Mapper mosaic. Photogrammetric Engineering and Remote Sensing 63: 59–67.

Horler DN, Ahern FJ. 1986. Forestry information content of thematic mapper data. International Journal of Remote Sensing 7: 405–428.

Jakubauskas ME. 1996. Thematic Mapper characterization of lodgepole pine seral stages in Yellowstone National Park, USA. Remote Sensing of Environment 56: 118–132.

Jordan CF. 1969. Derivation of leaf-area index from quality of light on the forest floor. Ecology 50: 663–666.

Kaneko D, Hino M. 1996. Proposal and investigation of a method for estimating surface energy balance in regional forests using TM derived vegetation index and observatory routine data. International Journal of Remote Sensing 17: 1129–1148.

Kanemasu ET, Heilman JL, Bagley JO, Powers WL. 1977. Using Landsat data to estimate evapotranspiration of winter wheat. Environmental Management 1: 515–520.

Kauth RJ, Thomas GS. 1976. The tasselled cap—a graphic description of the spectral-temporal development of agricultural crops as seen by Landsat. Pages 4B-41–4B-51 in Swain PH, Morrison DB, eds. Proceedings of the Second Annual Symposium on Machine Processing of Remotely Sensed Data, Purdue University Laboratory for Applications of Remote Sensing, West Lafayette, IN, 6 June–2 July 1976. New York: Institute of Electrical and Electronics Engineers.

Lathrop RG, Pierce LL. 1991. Ground-based canopy transmittance and satellite remotely sensed measurements for estimation of coniferous forest canopy structure. Remote Sensing of Environment 36: 179–188.

Law BE, Turner D, Lefsky M, Campbell J, Guzy M, Sun O, Van Tuyl S, Cohen WB. Carbon fluxes across regions: Observational constraints at multiple scales. In Wu J, Jones B, Li H, Loucks O, eds. Scaling and Uncertainty Analysis in Ecology: Methods and Applications. New York: Columbia University Press. Forthcoming.

Lee K, Lee GB, Tyler EJ. 1988. Determination of soil characteristics from thematic mapper data of a cropped organic-inorganic soil landscape. Soil Science Society of America Journal 52: 1100–1104.

Lefsky M, Cohen WB, Spies T. 2001. An evaluation of alternative remote sensing products for forest inventory, monitoring, and mapping of Douglas-fir forests in western Oregon. Canadian Journal of Forest Research 31: 78–87.

Li X, Strahler AH. 1985. Geometric-optical modeling of a conifer forest canopy. IEEE Transactions on Geoscience and Remote Sensing 23: 705–721.

Lunetta R, Lyon J, Guindon B, Elvidge C. 1998. North American Landscape Characterization dataset development and data fusion issues. Photogrammetric Engineering and Remote Sensing 64: 821–829.

Lymburner L, Beggs P, Jacobson C. 2000. Estimation of canopy-average surface-specific leaf area using Landsat TM data. Photogrammetric Engineering and Remote Sensing 66: 183–191.

Mack E, Firbank L, Bellamy P, Hinsley S, Veitch N. 1997. The comparison of remotely sensed and ground-based habitat area data using species-area models. Journal of Applied Ecology 34: 1222–1228.

Malila WA. 1980. Change vector analysis: An approach for detecting forest changes with Landsat. Pages 326–335 in Burroff PG, Morrison DB, eds. Proceedings of the Sixth Annual Symposium on Machine Processing of Remotely Sensed Data and Soil Information Systems and Remote Sensing and Soil Survey, Purdue University, Laboratory for Applications of Remote Sensing, West Lafayette, IN, 3–6 June 1980. New York : Institute of Electrical and Electronics Engineers.

Maselli F, Rodolfi A, Bottai L, Conese C. 1996. Evaluation of forest fire risk by the analysis of environmental data and TM images. International Journal of Remote Sensing 17: 1417–1423.

May A, Pinder JI, Kroh G. 1997. A comparison of Landsat Thematic Mapper and SPOT multi-spectral imagery for the classification of shrub and meadow vegetation in northern California, U.S.A. International Journal of Remote Sensing 18: 3719–3728.

McComb W, McGrath M, Spies T, Vesely D. 2002. Models for mapping potential habitat at landscape scales: An example using northern spotted owls. Forest Science 48: 203–216.

McGwire K, Friedl M, Estes JE. 1993. Spatial structure, sampling design and scale in remotely-sensed imagery of a California savanna woodland. International Journal of Remote Sensing 14: 2137–2164.

McRoberts R, Wendt D, Nelson M, Hansen M. 2002. Using a land cover classification based on satellite imagery to improve the precision of forest inventory area estimates. Remote Sensing of Environment 81: 36–44.

Nemani RR, Running SW. 1989. Testing a theoretical climate–soil–leaf area hydrologic equilibrium of forests using satellite data and ecosystem simulation. Agriculture and Forest Meteorology 44: 245–260.

Oetter D, Cohen WB, Berterretche M, Maiersperger T, Kennedy R. 2001. Land cover mapping in an agricultural setting using multiseasonal Thematic Mapper data. Remote Sensing of Environment 76: 139–155.

Olsson H. 1994. Changes in satellite-measured reflectances caused by thinning cuttings in boreal forest. Remote Sensing of Environment 50: 221–230.

Poole K, Wakelyn L, Nicklen P. 1996. Habitat selection by lynx in the Northwest Territories. Canadian Journal of Zoology 74: 845–850.

Rock BN, Vogelmann JE, Williams DL, Vogelmann AF, Hoshizaki T. 1986. Remote detection of forest damage. BioScience 36: 439–445.

Rouse JW, Haas RH, Schell JA, Deering DW, Harlan JC. 1974. Monitoring the Vernal Advancement and Retrogradation (Greenwave Effect) of Natural Vegetation. College Station (TX): Texas A&M University, Remote Sensing Center. Report RSC 1978-4.

Sader SA, Powell GV, Rappole JH. 1991. Migratory bird habitat monitoring through remote sensing. International Journal of Remote Sensing 12: 363–372.

Silbernagel J, Martin S, Gale M, Chen J. 1997. Prehistoric, historic, and present settlement patterns related to ecological hierarchy in the eastern Upper Peninsula of Michigan, U.S.A. Landscape Ecology 12: 223–240.

Skidmore A, Varekamp C, Wilson L, Knowles E, Delaney J. 1997. Remote sensing of soils in a eucalypt forest environment. International Journal of Remote Sensing 18: 39–56.

Skole D, Tucker C. 1993. Tropical deforestation and habitat fragmentation in the Amazon: Satellite data from 1978 to 1988. Science 260: 1905–1910.

Smith MO, Ustin SL, Adams JB, Gillespie AR. 1990. Vegetation in deserts, I: A regional measure of abundance from multispectral images. Remote Sensing of Environment 31: 1–26.

Spies TA, Reeves GH, Burnett KM, McComb WC, Johnson KN, Grant G, Ohmann JL, Garman SL, Bettinger P. 2002. Assessing the ecological consequences of forest policies in a multi-ownership province in Oregon. Pages 179–207 in Liu J, Taylor WW, eds. Integrating Landscape Ecology into Natural Resource Management. Cambridge (United Kingdom): Cambridge University Press.

Stanfield B, Bliss J, Spies T. 2002. Land ownership and landscape structure: A spatial analysis of sixty-six Oregon (USA) Coast Range watersheds. Landscape Ecology 17: 685–697.

Steininger M. 2000. Satellite estimation of tropical secondary forest above-ground biomass: Data from Brazil and Bolivia. International Journal of Remote Sensing 21: 1139–1157.

Turner D, Gower S, Cohen WB, Gregory M, Maiersperger T. 2002. Effects of spatial variability in light use efficiency on satellite-based NPP monitoring. Remote Sensing of Environment 80: 397–405.

Vogelmann J, Howard S, Yang L, Larson C, Wylie B, Van Driel N. 2001. Completion of the 1990 National Land Cover Data Set for the conterminous United States from Landsat Thematic Mapper data and ancillary data sources. Photogrammetric Engineering and Remote Sensing 67: 650–662.

Williams DL, Nelson RF. 1986. Use of remotely sensed data for assessing forest stand conditions in the eastern United States. IEEE Transactions on Geoscience and Remote Sensing 24: 130–138.

Woodcock CE, Strahler AH. 1987. The factor of scale in remote sensing. Remote Sensing of Environment 21: 311–332.