Remote sensing for large-area habitat mapping

Gregory J. McDermid[1], Steven E. Franklin[2] and Ellsworth F. LeDrew[3]

[1]Department of Geography, University of Calgary, Calgary, AB T2N 1N4, Canada
[2]Department of Geography, University of Saskatchewan, Saskatoon, SK S7N 5A5, Canada
[3]Department of Geography, University of Waterloo, Waterloo, ON N2L 3G1, Canada

Abstract: Remote sensing has long been identified as a technology capable of supporting the development of wildlife habitat maps over large areas. However, progress has been constrained by underdeveloped linkages between resource managers with extensive knowledge of ecology and remote sensing scientists with backgrounds in geography. This article attempts to traverse that gap by (i) clarifying the imprecise and commonly misunderstood concept of 'habitat', (ii) exploring the recent use of remote sensing in previous habitat-mapping exercises, (iii) reviewing the remote sensing toolset developed for extracting information from optical satellite imagery, and (iv) outlining a framework for linking ecological information needs with remote sensing techniques.

Key words: habitat mapping, remote sensing, scene models, vegetation structure.

I Introduction

Environmental management and conservation agendas commonly include requirements for mapping and monitoring wildlife habitat for the purpose of estimating population sizes, identifying critical habitat, and predicting the impacts of environmental change. While occasionally conducted over small geographic areas (e.g., Radeloff *et al.*, 1999; Lauver *et al.*, 2002) these initiatives commonly require regional, or, increasingly, global perspectives that defy traditional field-based techniques (e.g., Skidmore and Gauld, 1996; Corsi *et al.*, 1999; Osborne

et al., 2001). In light of these challenges, remote sensing has often been identified as a key data source for supporting habitat mapping and other large-area ecological applications (Graetz, 1990; Roughgarden *et al.*, 1991; Wickland, 1991). The promise of the technology lies in its potential to deliver information about key ecological drivers over large areas with regular temporal revisit periods. These sentiments are reflected in the growing number of 'integrated' remote sensing-ecology studies in the literature (e.g., Hines and Franklin, 1997; Carroll *et al.*, 1999;

Kobler and Adamic, 1999; Skidmore, 2002). However, the technology remains a 'blunt tool' (Plummer, 2000) requiring a significant amount of multidisciplinary research and joint understanding in order to reach its full potential.

Multidisciplinary approaches to science and management are tremendously appealing, because they bring together individuals with different experience and backgrounds whose constructive exchange of ideas have the potential to generate novel solutions. However, such projects are often challenging in that people entering new disciplines often do not possess the necessary background knowledge, and lack the ability to communicate effectively with their new peers. Such is clearly the case with the remote sensing-ecology interface, where significant gaps of understanding exist between the 'tools' experts – practitioners of remote sensing, GIS, and other spatial techniques – and ecologists. Plummer (2000) lamented the issue in the context of ecological process models, but a wider survey of the literature reveals this to be a common pattern. In their review of remote sensing protocols used in the national Gap Analysis Program, Eve and Merchant (1998) offered the following advice to new projects just getting under way with their ecological mapping: 'Brace yourself and good luck!'

There is a need for users and producers of remotely sensed information to seek common ground with respect to the capabilities of the tools. Hoffer (1994) referred to the 'information needs definition circle' (Figure 1) in which resource managers and remote sensing/GIS specialists – lacking a common background and thorough understanding of each other's field – struggle to communicate with one another. The resource manager requires a variety of information products at a wide range of scales but is unsure of the capabilities of remote sensing and GIS, and so asks 'What can the tools do to help me?' The remote sensing specialist, unfamiliar with the complex intricacies of ecology and ecosystem processes, asks in turn 'What type of information do you need?'

This paper attempts to traverse that knowledge gap, looking specifically at the use of remote sensing and other geospatial tools for large-area habitat mapping. It begins with definitions of the basic concepts and relevant terms, continues with a review of remote sensing in habitat mapping projects and common information extraction techniques, and concludes with the description of a framework for linking environmental information needs with remote sensing strategy through hierarchy theory and the remote sensing scene model.

II Definitions and nomenclature

In 1942, Raymond Lindeman penned a landmark paper that defined ecosystem as 'the system composed of physical-chemical-biological processes active within a space-time unit of any magnitude, i.e., the biotic community plus its abiotic environment'. While the definition is not strictly spatial, it is generally understood that the area referred to by an ecosystem is a common and recognizable environmental unit. 'Habitat', in turn, occupies a somewhat adjunct position, referring specifically to the place or physical environment occupied by a population of organisms (Colinvaux, 1986). Unfortunately, the two terms have become so ubiquitous over time that their potential for misuse is high. For example, authors in the remote sensing community are quick to label their classification products 'habitat maps' whenever the work falls within an ecological context (e.g., Dechka *et al.*, 2000; Vinluan and de Alban, 2001) when, in many cases, the term 'land cover maps' (Wyatt *et al.*, 1994) might be more appropriate. However, the issue is complicated, being hampered in practice by multiple definitions and frequent inconsistencies in the literature.

The fact that habitat is rarely defined suggests that its meaning is generally taken for granted, yet even a simple dictionary search reveals two different definitions: one relating

Figure 1   The information needs definition circle
Source: Adapted from Hoffer (1994).

to location – the place where a species is commonly found – and the other relating to condition – the type of environment in which an organism normally occurs (Merriam-Webster, 1998). While Morrison *et al.* (1992) noted this initial dichotomy, a survey of the literature reveals an even more complicated situation. Corsi *et al.* (2000) partitioned the various meanings of habitat into a nine-cell matrix (Table 1), showing that the term can refer to a distinct species or community (e.g., grizzly bear habitat), or a land attribute with no relation to biota (e.g., riparian habitat). Specific definitions can also include elements of Cartesian space, environmental space, or both. The situation is further complicated by frequent examples of ambiguity in the litera-ture; sometimes within the same publication. For example, Lehmkuhl and Raphael (1993) used the terms 'old-forest habitat' and 'owl habitat' simultaneously in a paper about northern spotted owls in the Olympic Peninsula. All of the above contributes to misunderstanding amongs multidisciplinary colleagues, and prompted Hall *et al.* (1997) to issue a plea for standard terminology.

Corsi *et al.* (2000) speculated that the origin of the word habitat – Latin for *habitare*, or 'to dwell' – reflects its initial purpose as a term to describe the environment a species lives in. Its gradual transformation into more of a land-based concept is likely related to the emergence of widespread habitat and biodiversity mapping, in which individual maps for every species are virtually impossible to produce (Kerr, 1986). The term 'habitat type', defined as a mappable unit of land homogeneous with respect to vegetation and environmental factors (Jones, 1986), is a likely product of this trend. In retrospect, this context likely forms the basis of many remote sensing 'habitat maps', and subsequent confusion over the use of the term.

Considered carefully, the value of habitat type maps is based on the assumption that an area exhibiting similar vegetation cover is also likely to contain homogeneous conditions with respect to other environmental gradi-ents. However, it seems unlikely that the variation of factors affecting the distribution of all species is completely interdependent, which would lead one to conclude that habi-tat types are not truly homogeneous. It also seems reasonable to speculate that the focus on habitat types as an ecological mapping unit may have arisen from an early lack of sophisticated spatial tools capable of portray-ing the many environmental factors that

Table 1   The various meanings of the term 'habitat', with selected references from the literature (modified after Corsi *et al.*, 2000)

| | Biota | | Land |
	Species	Species and communities	
Cartesian space	Begon *et al.*, 1990; Krebs, 1985; Odum, 1971	Zonneveld, 1995	
Environmental	Collin, 1988; Whittaker *et al.*, 1973; Moore, 1967		
Environmental and Cartesian	Morrison *et al.*, 1992; Mayhew and Penny, 1992	Yapp, 1922; Colinvaux, 1986	Stelfox and Ironside, 1982; USFWS, 1980a; 1980b; Herr and Queen, 1993

affect the distribution of species, such as land cover, soil type, temperature variability, food availability, and shelter (among many others) (Corsi *et al.*, 2000). The recent development of GIS technology, however, has revolutionized the feasibility of these more sophisticated environmental characterizations, and a subsequent revival of the original species-specific meaning of habitat. Given these observations, we will adopt the following definition, after Hall *et al.* (1997):

> Habitats are the resources and conditions present in an area that produce occupancy, including survival and reproduction, by a given organism, and, as such, imply more than vegetation and vegetation structure. A habitat is the sum of the specific resources that are needed by an organism.

As a result, habitat is considered to be a species-specific concept, and includes elements of both environmental and Cartesian space. Table 2 presents a summary of habitat-related terminology, including several not discussed directly in this work, but commonly encountered in the ecological literature.

It is useful to consider the relationship between the 'habitat' concept and that of 'land cover': the attribute most commonly mapped with remote sensing methods. Land cover is generally defined as the observed (bio)physical description of the earth's surface

(DiGregio and Jansen, 2000). While land cover is often the first data layer produced in a mapping exercise, it is usually desirable to combine this information with additional ancillary data in order to derive other spatial products that are more useful to managers and researchers. A good example of this is the transformation of land *cover* to land *use*, which describes not only the physical and biological cover of an area, but also contains information on how the land is used by humans. The transformation can either be accomplished indirectly through implied relationships, or directly through the integration of other spatially referenced information (Jensen and Cowen, 1999).

From the practical perspective of a remote sensing scientist, the relationship between land cover and habitat is analogous to that which exists between land cover and land use. Habitat (or other ecological properties) can either be inferred from land cover indirectly or modelled explicitly through integration with other environmental factors (Corsi *et al.*, 2000). The ecological literature contains examples of both strategies.

III Habitat mapping with remote sensing: a review
A survey of the literature reveals a variety of remote sensing strategies applied to habitat

Table 2 Habitat terminology (modified after Krausman, 1999)

Term	Definition
Habitat	The sum and location of the specific resources needed by an organism for survival and reproduction
Habitat type	A mappable unit of land considered homogeneous with respect to vegetation and environmental factors
Habitat use	The way an organism uses the physical and biological resources in a habitat
Habitat selection	A series of innate and learned behavioural decisions made by an animal about what habitat it would use
Habitat preference	The consequences of habitat selection
Habitat availability	The accessibility and procurability of the physical and biological components of a habitat
Habitat suitability	The ability of the habitat to sustain life and support population growth
Habitat quality	The ability of the environment to provide conditions appropriate for individual and population persistence
Critical habitat	A legal term describing the physical or biological features essential to the conservation of a species, which may require special management considerations or protection

mapping projects spanning a wide range of spatial scales (Table 3). Manual interpretation of aerial photographs has often been employed by studies that involve species with limited ranges and/or the analysis of relatively small areas. For example, Palma *et al.* (1999) used manual interpretation of 1:10 000 photography to extract a variety of environmental variables including landcover, landcover diversity, road density, and drainage density to characterize the habitat immediately surrounding confirmed sightings of Iberian lynx in the western Algarve region of Portugal. Lauver *et al.* (2002) used 1:12 000 digital orthophotos to map detailed environmental variables such as tree density and hedgerow location in order to assess loggerhead shrike habitat suitability over a 40 000 ha study area in Kansas. In both these cases, remote sensing served primarily as a complement to field surveys, and made use of skilled interpreters to generate detailed, high-quality information. Unfortunately, the labour-intensive nature of such manual procedures tends to limit the range over which this type of analysis can be conducted.

Researchers faced with larger study areas have typically turned to digital processing of medium-spatial-resolution satellite imagery such as Landsat Multispectral Scanner (MSS), Thematic Mapper (TM), or Enhanced Thematic Mapper Plus (ETM+) for more efficient acquisition of environmental information. Landcover, in particular, plays a prominent role in most regional-scale habitat studies. McClain and Porter (2000), for example, used TM-derived landcover maps to evaluate white-tailed deer habitat in the Adirondacks of New York. A second study by Nielsen *et al.* (2003) used resource selection functions to link grizzly bear location data to a landcover map covering more than 10 000 km^2 in the foothills of Alberta, Canada. However, while landcover maps may contain useful predictive power, they are often not capable of revealing the underlying mechanisms and dynamic nature of complex natural landscapes.

Several researchers have attempted to supplement basic landcover information with fragmentation metrics, topographic measures, and vegetation indices, among others.

Table 3   Literature examples showing the range of scales and remote sensing-derived variables used in previous habitat mapping projects

	Local	Regional	National/Continental
Land cover	Palma *et al.*, 1999; Radeloff *et al.*, 1999; Lauver *et al.*, 2002	Hines and Franklin, 1997; Roseberry, 1998; Kurki *et al.*, 1998; Carroll *et al.*, 1999; Smith *et al.*, 1998; McClain and Porter, 2000; García Borboroglu *et al.*, 2002; Ciarniello *et al.*, 2002; Danks and Klein, 2002; Norris *et al.*, 2002; Rushton *et al.*, 1997; Woolf *et al.*, 2002; Nielsen *et al.*, 2003	Osborne *et al.*, 2001
Topography	Palma *et al.*, 1999	Ciarniello *et al.*, 2002; Danks and Klein, 2002; Woolf *et al.*, 2002; Nielsen *et al.*, 2003	Osborne *et al.*, 2001
Fragmentation	Radeloff *et al.*, 1999; Palma *et al.*, 1999	Hines and Franklin, 1997; Roseberry, 1998; Kurki *et al.*, 1998; Hargis *et al.*, 1999; Woolf *et al.*, 2002	
Vegetation greenness/phenology		Verlinden and Masogo, 1997; Ciarniello *et al.*, 2002	Wallin *et al.*, 1992
Vegetation structure	Radeloff *et al.*, 1999; Lauver *et al.*, 2002	Hines and Franklin, 1997; Carroll *et al.*, 1999	

For example, Danks and Klein (2002) used the topographic variables elevation, slope, aspect, and ruggedness to develop predictive models of muskoxen habitat in northern Alaska. Other studies have demonstrated the value of fragmentation metrics as indicators of habitat structure. For example, Hargis *et al.* (1999) employed a suite of spatial statistics to investigate the effects of forest fragmentation on American martens in the Uinta Mountains of Utah. In a later study, Hansen *et al.* (2001) explored the spatial effects of timber harvesting on woodland caribou habitat in southeastern British Columbia, Canada. While these approaches seem capable of summarizing complex spatial habitat requirements, the challenge involves selecting the correct metrics and identifying the appropriate scale of observation.

The challenge of balancing the need for detailed information with the cost and complexities involved with producing such information increases directly with study area size. Habitat projects operating at the national and continental level are often forced by practical reasons to use more generalized variables from coarse-resolution satellite data. For example, Wallin *et al.* (1992) used the Normalized Difference Vegetation Index (NDVI) of 4 km AVHRR imagery in their analysis of breeding habitat for the red-billed quelea in sub-Saharan Africa. The authors hypothesized that NDVI would be capable of providing a reasonable index of more detailed (and unavailable) measures such as vegetation condition and food availability.

The growing demand for large area environmental information is reflected by the numerous large-area data initiatives, including landcover maps of the United States (Loveland *et al.*, 1991), Canada (National Resources Canada, 1995), and the world

(Hansen *et al.*, 2000); the Pathfinder (Maiden, 1994; James and Kalluri, 1994) and MODIS (Justice and Townshend, 2002) data sets; and the National Gap Analysis Program (Scott *et al.*, 1993). However, these data are likely to lack the spatial grain and environmental detail necessary for most habitat-mapping projects.

At the leading edge of the discipline are studies that have attempted to incorporate detailed vegetation attributes such as taxonomy, age, and structure derived from widely available satellite imagery. The work by Carroll *et al.* (1999) stands out with its use of sophisticated TM-derived estimates of canopy closure, tree size, and percent conifer in a study of fisher habitat in the Klamath region of Oregon and California. In similar works, Hines and Franklin (1997) and Franklin and Stephenson (1996) demonstrated the value of a high-quality, regional-scale (2 million ha) vegetation database in the San Bernardino Mountains of southern California that included spatially detailed information on forest cover (landcover, fragmentation) and canopy structure (canopy coverage, tree crown size) with an analysis of habitat quality for the California spotted owl.

While obviously expensive and difficult to produce, large-area vegetation databases with at least moderate levels of structural and taxonomic detail are likely required for most large-area habitat studies. Deriving such databases is a tremendous challenge that requires the intelligent coupling of ecological theory and remote sensing technique.

IV Remote sensing information extraction strategies

The application of remote sensing techniques to large-area habitat projects is often hindered by the relative immaturity of the RS/GIS discipline. Researchers both inside and outside the field tend to forget that we have only been working with earth-observing satellites for about 30 years, and that truly large-area projects (those combining information from two or more adjacent scenes) have only been widely attempted within the past decade.

Several works (e.g., Meyer and Werth, 1990; Mladenoff and Host, 1994) have criticized the 'overselling' of Landsat data, citing the inconsistent delineation of species composition and detailed vegetation structure, among other issues. In response, some specialists have pointed to the vast technical gains over early MSS instruments (Hoffer, 1994), improved algorithms (e.g., Bolstad and Lillesand, 1992; Cohen *et al.*, 1995; 2003), and the introduction of new sensor technologies (e.g., Asner *et al.*, 2000; Lim *et al.*, 2003). Others (e.g., Trotter, 1991) have questioned the necessity for 'higher accuracy' map products destined for use with data of lesser or unspecified quality. Regardless of the debate, ecologist and resource managers require at least a basic understanding of the techniques and capabilities of remote sensing. Together, these constitute the 'toolset' for large-area habitat mapping.

1 Classification

Image classification – the systematic grouping of remote sensing and other geographically referenced data by categorical or, increasingly, fuzzy decision rules – is the best-known and most widely used information extraction technique in remote sensing. Given a choice, many technicians prefer classification, because (i) the methodological procedures are widely known, (ii) the output is generally simple to understand, and (iii) the accuracy of the results are relatively easy to assess.

The vegetation attributes typically mapped through classification include a general typing of physiognomy and dominant species composition. These are reviewed in detail by S.E. Franklin (2001), and are generally broken down hierarchically into broad classes of landcover at Level I (e.g., forest, nonforest, water), forest types at Level II (e.g., conifer, broadleaf, mixed forest), and more detailed species composition/canopy structure criterion at Level III (e.g., open-canopy spruce, closed-canopy spruce, trembling aspen). While consistent separation at Level III is challenging (J. Franklin *et al.*,

2003), particularly over mixed forest targets (Reese *et al.*, 2002), acceptable accuracies can generally be obtained with the correct image processing procedures (e.g., Brown de Colstoun *et al.*, 2003).

There are literally dozens – if not hundreds – of classification techniques used in the processing of remotely sensed imagery, and they are well described by other works (e.g., Jensen, 1996; Mather, 1999). The purpose of this review is not to duplicate those efforts, but rather to provide a summary of the major choices required for all classification projects, paying particular attention to the use of imagery over large areas.

a Variable selection: Satellite remote sensing instruments deliver spectral measures that are highly related to landcover, and represent a powerful data set for mapping surface patterns across broad regions (e.g., DeFries and Belward, 2000; Lunetta *et al.*, 2002; Cihlar *et al.*, 2002; Walker *et al.*, 2002; Homer *et al.*, 2002). However, the successful application of these data depends largely on the selection of appropriate mapping variables. Raw spectral values can undergo a wide variety of mathematical transformations including principal components (Fung and LeDrew, 1987; Piwowar and LeDrew, 1996), tasseled cap (Crist and Cicone, 1984), and band ratioing (Satterwhite, 1984) techniques designed to reduce data dimensionality, subsume noise, and enhance specific spectral phenomenon. These data can often also benefit from a variety of textural (Haralick *et al.*, 1973; Irons and Peterson, 1981; Clausi, 2002), contextual (Binaghi *et al.*, 1997), and other (Read and Lam, 2002) pattern recognition techniques aimed at capturing additional information in the spatial domain. Numerous studies have also demonstrated the utility of spatially referenced ancillary data for classification, including topography, climate, geology, landform, and soils (e.g., Franklin and Moulton, 1990; McDermid and Franklin, 1995; Treitz and Howarth, 2000; Gould *et al.*, 2002). Multitemporal analysis – the integration

of scenes acquired at different seasons – is often applicable, particularly for detailed forest species discrimination at the stand level (e.g., Wolter *et al.*, 1995; Brown de Colstoun *et al.*, 2003).

b Supervised versus unsupervised classification: Classification approaches can generally be considered as either supervised, unsupervised, or hybrid (Fleming and Hoffer, 1975). Unsupervised routines are designed to illuminate the natural groupings or clusters present in the mapping variables, and require no prior knowledge of the study area. Supervised classification techniques, in contrast, use intensive hands-on training in an attempt to extract predefined information classes from the explanatory variables, and, as such, require specific *a priori* knowledge.

Because of the reduced need for spatially detailed ground information, many large-area mapping projects have relied heavily on unsupervised techniques. A survey of 21 participants in the National Gap Analysis Program who used pure classification approaches as their primary mapping protocol revealed that 41% used unsupervised classification, compared to just 5% for supervised classification (Eve and Merchant, 1998). Unfortunately, the benefits of the unsupervised technique are often outweighed by the difficulty of postclassification labelling (which itself requires substantial ground information) and the procedure has often been shown to produce suboptimal results. Huang *et al.* (2003) compared the accuracy of two large-area mapping projects in Utah: one 9-scene application that was classified with a supervised technique, and one 14-scene area classified with unsupervised criterion. While other factors almost certainly played a role, the authors attributed at least some of the roughly 8% overall accuracy improvement to the high-quality training data employed in the supervised classification.

The potential conflict between spectral clusters and desired information classes – combined with the difficulty of obtaining

abundant training data over broad areas – has encouraged many researchers to employ hybrid supervised/unsupervised elements to their strategy. Reese *et al.* (2002) used 'guided clustering' in the production of a 12-scene landcover map of Wisconsin from Landsat TM data. The approach involved the application of an unsupervised routine on training pixels for which the information class was already known. Clusters were merged on the basis of transformed divergence values, spectral space plots, and visual assessment. Eventually, all of the subsets for each information class were assembled into unique signature sets, which were then applied in a standard maximum likelihood classification. Using these methods, the authors were able to achieve overall classification accuracies in the range of 70% to 84% for Anderson Level II/III landcover classes. Early successes with these hybrid methods in the GAP program (e.g., Lillesand, 1994) led to their subsequent adoption by 48% of the states surveyed.

c Decision rules: All remote sensing classifiers operate as pattern recognition algorithms that rely on decision rules to define boundaries and assign class membership. While these rules can be organized along a variety of lines, the parametric/nonparametric categorization presents a convenient basis for discussion.

Many of the most familiar classifiers operate in Euclidean space, and rely on statistical measures such as central tendency, variance, and covariance to perform their functions. These routines – clustering algorithms, discriminant functions, and maximum likelihood, for example – are robust and well behaved when the input variables conform to basic statistical assumptions, but may perform poorly in the presence of nonparametric distributions (Peddle, 1995). The maximum likelihood classifier (MLC) is perhaps the best known of the parametric classifiers. A supervised technique, MLC uses training to characterize information classes on the basis of the mapping variables' mean values and covariance matrices. In the decision phase, unknown pixels are assigned a probability-of-membership for each class, and placed in the 'most likely' category. While the sensitivity of MLC to variables with nonparametric – particularly multimodal – distributions is well known, the technique remains very popular. In practice, many of the normality issues can be resolved by prestratifying the imagery with ancillary data (Hutchinson, 1982; Harris and Ventura, 1995) or unsupervised classification (Homer *et al.*, 1997). However, these procedures can become unwieldy, and MLC remains incapable of incorporating low-level (nominal, ordinal) data directly.

Researchers have invested a significant amount of effort in the search for decision rules free of parametric constraints. The nearest neighbour (NN, or kNN) classifier is a supervised technique that assigns unknown observations to the class of the nearest training vector (or majority of k vectors), and has proven effective in several recent studies (e.g., Kuncheva and Jain, 1999; Barandela and Juarez, 2002). However, NN classifiers are computationally intensive and highly susceptible to errors in training data (Brodley and Friedl, 1999).

Artificial neural networks (ANNs) are a second nonparametric approach to classification that has recently received a lot of attention in the remote sensing literature (e.g., Ripley, 1996; Atkinson and Tatnall, 1997; Murai and Omatu, 1997; Kimes *et al.*, 1999). The technique falls within a group of machine learning classifiers that 'learn' decision rules through training observations without statistical constraints. ANNs learn patterns by iteratively considering the multivariate characteristics of each class, multiplying the explanatory variables by a set of weights, applying a transfer function to their weighted sum, and using these to predict the identity of the original training data. Subsequent iterations are designed to improve the fit between actual and predicted class membership, and increase the utility of the classifier. One of the strengths of ANNs lies in their ability to handle information categories that

consist of many spectral subclasses without the explicit stratifying that would be necessary with parametric techniques such as MLC (Pax-Lenney *et al.*, 2001). However, many technicians are uncomfortable with the 'black box' nature of ANNs, and they remain poorly integrated into most commercial image processing packages (J. Franklin *et al.*, 2003).

Decision trees are another of the 'machine learning' classifiers, but are far more conceptually transparent than ANNs. Decision trees handle classification by recursively partitioning a data set into smaller and smaller subdivisions on the basis of tests performed at branches or nodes in a tree (Hansen *et al.*, 1996). The tree is composed of a root node (composed of all the data), a set of internal nodes (splits), and a set of terminal nodes (leaves). Within this framework, an image is classified by sequentially subdividing it according to the decision framework defined by the tree (Friedl and Brodley, 1997). Decision trees work well when the boundaries between classes have well-defined thresholds, and are capable of handling large numbers of dependent variables of all data levels (Fayyad and Irani, 1992). S.E. Franklin *et al.* (2001) modified the decision tree concept somewhat in a large-area classification of landcover in Alberta by selectively combining parametric (ML), nonparametric (kNN), and GIS decision rule criteria where conditions for each method were optimal. This study (S.E. Franklin *et al.*, 2001) and others (e.g., Borak and Strahler, 1999; Rogan *et al.*, 2002) have found decision trees to outperform both MLC and other nonparametric classifiers.

d Hard versus soft classification: The natural world is a heterogeneous place that does not easily lend itself to the nominal information scales imposed by classification. Traditional 'hard' classifiers use binary logic to determine class membership, in that each observation can belong to one and only one category. Classification strategies that employ fuzzy logic, by contrast, assign observations membership in each category (Foody, 1996a; 1999). The result is a more conceptually appealing classification model that seems better capable of representing the 'partial truth' that we observe in the real world. For example, white spruce and trembling aspen species often blend together into mixed stands in the forests of western Alberta, and create a problem for traditional classification schemes. A hard classifier might address the issue by establishing a 'mixed' forest class through the placement of decision boundaries along the species composition continuum – made up of, say, stands with more than 25% coniferous trees, but less than 75%. Under this scenario, a stand with 25% conifers would be considered pure, while a stand with 26% would be called mixed. A fuzzy classifier, on the other hand, could soften these decision boundaries by allowing mixed observations to have membership in each class. Even probabilistic classifiers (like MLC) that are not based on fuzzy set theory can have their decision boundaries 'softened' by retaining the class probability values (Foody, 1996b).

While fuzzy and other soft classification techniques are appealing, they also face challenges. For example, visualizing the results of a fuzzy classification for the purpose of decision making or thematic map production often requires a 'defuzzification' process in order to assign observations into definitive classes. Developing methods to better incorporate fuzzy information for ecosystem management and landscape planning still requires more research (J. Franklin *et al.*, 2003).

2 Sub-pixel models

While nominal compilations of vegetation at the stand level are normally the domain of image classification procedures, the more detailed biophysical attributes of vegetation are usually better handled by per-pixel models. There are two primary reasons for this: first, the vegetation elements normally considered at this level – LAI, biomass, crown closure, volume, density, etc. – vary continuously

across the landscape and are not well represented by categorical measures; second, attributes at this level of detail are commonly smaller than the pixel size of optical satellite imagery. While detailed structural/biophysical factors can be summarized at the stand level and mapped discretely through classification, models that estimate biophysical attributes on a continuum provide much more flexibility with regard to their future use. One can also argue that pixel-based outputs present a more realistic spatial characterization of tree/gap-level information. Cohen *et al.* (2001) used TM imagery and empirical models to map percent conifer, crown diameter, and age across 5 million hectares of forest in western Oregon. Besides generating a seamless output over the entire study area, their methods resulted in a forest information database with exceptionally flexibility. By maintaining high-order information, the system provides managers with divergent needs the opportunity to define categories that suit their individual application. For example, one manager might use the system to define a GIS layer composed of three age classes: <80 years, 80–200 years, and >200 years (Cohen *et al.*, 1995). While this suits the needs of the first application, a second perspective user may only require two categories, or perhaps three classes with different thresholds.

While simple regression analysis is the most popular method for estimating sub-pixel properties from remote sensing data, it is certainly not the only one. Recent work has illustrated the effectiveness of alternative regression procedures such as canonical correspondence analysis (Cohen *et al.*, 2003; Ohmann and Gregory, 2002), generalized linear models (J. Franklin, 1995; Moisen and Edwards, 1999), and generalized additive models (Frescino *et al.*, 2001; Edwards *et al.*, 2002) that are capable of incorporating nonlinear, categorical, or other nonparametric data into the analysis. Mixture models are commonly used to map the fraction of scene elements across an image (e.g., Mustard, 1993; Huguenin *et al.*, 1997) and can be linked

with physical scene models to estimate specific structural attributes (e.g., Peddle *et al.*, 1999).

One of the dangers of the modelling approach is the illusion of precision afforded by continuous variable estimation. The experience of many researchers (e.g., Peterson *et al.*, 1987; Cohen and Spies, 1992; S.E. Franklin and McDermid, 1993; S.E. Franklin *et al.*, 2003) has shown that there are definite limitations to the extent with which specific tree/gap parameters can be characterized by moderate-resolution sensors. This is particularly true in closed stands, where changes in the physical variable may not translate to a measurable difference in the canopy. While these limitations can be ameliorated somewhat through the use of other (nonspectral) environmental variables into the modelling process (J. Franklin, 1995), specific care must be taken to guard against overextending the limits of the data.

3 Quantifying landscape heterogeneity

While the great majority of remote sensing techniques are designed to extract knowledge concerning land composition and physical dimension, an important additional branch of digital processing is concerned with analysis of spatial structure. Scientists have long been aware that ecological processes are influenced by environmental patterns, and the subject of quantifying environmental heterogeneity has been an active research area for decades (e.g., Pielou, 1975). However, recent interest on the subject has increased dramatically, due to the complementary development of GIS and spatial statistics, coupled with the emergence of orbiting satellites as platforms for large-area ecological observations. It is within this context that the discipline of landscape ecology has emerged to examine landscape pattern, the influence of environmental actions on a landscape mosaic, and changes in landscape pattern and process over time (Turner *et al.*, 2001). Prominent among the discipline's core objectives are efforts to produce quantitative

measures of landscape heterogeneity, a pursuit that has culminated in the development of an impressive array of indices designed to capture the various nuances of spatial structure (e.g., McGarigal and Marks, 1995; Elkie *et al.*, 1999). A number of studies (e.g., Hargis *et al.*, 1999; Lawler and Edwards, 2002; Woolf *et al.*, 2002) have demonstrated the potential of these variables as predictors of habitat quality and other environmental concerns.

In spite of recent accomplishments, the effective quantification of environmental heterogeneity remains problematic (Gustafson, 1998). Despite – some would argue because of – the ready availability of software capable of generating large number of spatial pattern indices from many forms of digital maps, many researchers remain unclear regarding which metrics to use and what these measures might mean (Kepner *et al.*, 1995). Whereas early studies relied on as little as three core indices (e.g., O'Neill *et al.*, 1988), recent efforts commonly contain a much larger number of metrics (e.g., Luque *et al.*, 1994; Lawler and Edwards, 2002). In describing the functionality of the software package FRAGSTATS, McGarigal *et al.* (2002) describes well over 150 variables, divided into eight separate categories. Overwhelmed researchers have often turn to principal components analysis and other data reduction techniques to reduce redundancy and limit the amount of variables to a more reasonable number (Haines-Young and Chopping, 1996). For example, Riitters *et al.* (1995) used factor analysis to explore the redundancy of 55 landscape metrics derived from a variety of land-use and landcover maps, and concluded that close to 90% of the original variance could be explained by six univariate measures corresponding roughly to the first six factors of the analysis. The search for a relatively small number of meaningful variables that can be effectively applied to diverse landscapes remains an active research issue (Cushman *et al.*, unpublished data).

Even more elusive than the pursuit of parsimony is an understanding of the relationship between ecologically meaningful heterogeneity and that which can be mapped and measured by remote sensing. Spatial (and ecological) variability is a function of both scale and time; the observed structure of a natural landscape is dependent on the spatial resolution of the data (grain), the physical size of the study area (extent), and the time period over which observations were acquired (Gustafsen, 1998). Complexities surrounding the issue of scale is one of ecology's primary research focuses (e.g., Wiens, 1989; Allen and Hoekstra, 1992; O'Neill *et al.*, 1986; Hay *et al.*, 2002; Wu *et al.*, 2002).

4 Large-area challenges
Knowledge concerning the automated extraction of biophysical information from digital satellite imagery has been the mainstay of research in the remote sensing community for more than 30 years. However, while most would agree that these efforts have resulted in an impressive variety of useful techniques, the fact remains that many of our core procedures have never been thoroughly tested on data sets larger than a single image. Research involving information extraction over large areas – those consisting of two or more adjacent scenes – is currently one of the discipline's key frontiers (Cihlar, 2000; Woodcock *et al.*, 2001; Franklin and Wulder, 2003). The following is a brief overview of the core challenges presented by large-area studies.

a Image acquisition and temporal heterogeneity: The multiday temporal resolution of many earth-observing satellite systems creates a significant challenge for acquiring high-quality, cloud-free imagery over large study areas – particularly when there are specific temporal objectives. The inability to collect target scenes during specified time periods can derail certain information extraction techniques (multitemporal analysis, for example) and introduce unwanted variance to others.

Substituting historical imagery or data from alternate sensors – including SAR – is often required to meet specific mapping objectives, particularly in areas of persistent shadow or cloud cover (Wagner *et al.*, 2003; Franklin and Wulder, 2003).

Even under ideal conditions, study areas that traverse satellite path lines will have to deal with variability caused by temporal heterogeneity. Images acquired on different dates are likely to contain differences caused by changing ground conditions – moisture, vegetation phenology, and biomass (Schriever and Congalton, 1995) – in addition to atmospheric and illumination effects. All of these factors serve to complicate the mosaicking process and confound model and signature extension. While some of these issues can be accounted for in the image preprocessing phase, ground-based differences are difficult to overcome. Strategies for dealing with seam lines – abrupt changes between images caused in part by temporal heterogeneity – remains an active research issue.

b Image pre-processing: Radiometric processing in the form of atmospheric and/or topographic correction presents a significant challenge to large-area mapping and modelling activities, which require common radiometric scales across not only space and time, but potentially across sensors as well. Unfortunately, we presently lack a widespread standard for performing such adjustments. While much of the atmospheric correction literature is concerned with absolute calibration via radiative transfer models (e.g., Vermonte and Kaufman, 1995), the detailed atmospheric observations demanded by such solutions are rarely available. As an alternative, many users have come to rely on standard atmosphere parameterization from commercial image processing packages. However, this is often an unsatisfactory approach; commonly producing poor or unexpected results (Cohen *et al.*, 2001; McDermid *et al.*, unpublished data). Relative calibration procedures that

normalize 'slave' images to a high-quality 'master' through histogram matching (Homer *et al.*, 1997), dark object subtraction (Chavez, 1988), or linear transformation (Hall *et al.*, 1991; McGovern *et al.*, 2002) present an attractive set of alternatives.

Even less well defined is the role of topographic corrections over large areas. While topographically induced variance can be safely ignored over flat terrain, the effects can be significant in high-relief environments (Kimes and Kirchner, 1981; Allen, 2000). Numerous techniques have been devised to correct for terrain illumination differences, including simple cosine correction (S.E. Franklin, 1991) and the Minnaert correction (Tokola, *et al.*, 2001), among others (Civco, 1989; Conese *et al.*, 1993; Meyer *et al.*, 1993; Townshend and Foster, 2002). However, no geometry-based method seems capable of accounting for all topographic variation, since the issue is complicated by vegetation canopy geometry and the anisotropic behaviour of most cover types (Gu and Gillespie, 1998). At present, most large-area studies have chosen to ignore the topographic effect, dealing with it instead through stratification or the use of nonparametric methods that are less sensitive to its effects.

c Large-area diversity and spatial heterogeneity: In image classification, the concept of 'signature extension' represents the distance over which the training data from one location – say, a pine forest – can represent other similar locations across space (Jensen, 1996), and reflects the overall efficiency of the classification procedure. Spatial heterogeneity is the primarily limitation on signature extension; for example, phenological differences between pine forests at low elevation and those up high can create the need for additional high-cost training data, limit the ability to map consistent information classes, or both. The frequency with which these factors become an issue increases directly in proportion with the size and spatial detail of the mapping effort, and is one of the core challenges of large-area mapping exercises.

In many respects, large-area projects are crucibles of remote sensing efficiency. With limited resources, researchers are constantly challenging the limits of ground data, and pushing the envelope of spectral/temporal generalization. Previous studies have shown that spectral (Reese *et al.*, 2002) or physiographic (Homer *et al.*, 1997) stratification are the best strategies for maximizing efficiency over large, spatially heterogeneous study areas. Lillesand (1996) described the process of stratifying TM scenes into 'spectrally consistent classification units' that attempted to maximize both spectral and physiological homogeneity. Manis *et al.* (2001) developed 74 mapping zones across five southwest states (Utah, Nevada, New Mexico, Colorado, and Arizona) in support of the southwest GAP project. The goal of each of these efforts was twofold: (i) to partition massive volumes of data into manageable and logical units, and (ii) to improve the efficiency of vegetation modelling and landcover classification. Previous work in Minnesota by Bauer *et al.* (1994) showed that physiographic stratification improved overall classification accuracies by 10–15 %.

Image stratification coupled with robust and/or nonparametric information extraction techniques are the key strategies for dealing with large-area diversity and spatial heterogeneity. Digital elevation models, soils maps, census data, ecoregion zones, and previous classification products can all contribute to the stratification process. Operators must juggle diverse and potentially contradictory data sources, and define processing units that strike the correct balance between detail and cost.

d Accuracy assessment: The quality of a spatial data set is a broad issue that can relate to a variety of properties, including vagueness, precision, consistency, and completeness, among others (Worboys, 1998). The property of most frequent interest, however, is accuracy (Foody, 2002). That a map is not truly complete until its accuracy is properly assessed is one of the discipline's key tenets (Stehman and Czaplewiski, 1998; Cihlar, 2000).

Validation is the process of assessing – by independent means – the accuracy of remote sensing information products (Justice *et al.*, 2000), and the literature contains numerous references on the subject (see annotated bibliography by Veregin, 1989). However, very little has been done to assimilate the wide variety of techniques into a standard set of methodologies suitable for consistent application over large areas (Edwards *et al.*, 1998). Outstanding issues include the design of statistically valid and logistically feasible sampling strategies, the adoption of stable and widely understood accuracy metrics, the assessment of positional errors, and the determination of reference data accuracy (Franklin and Wulder, 2003).

Ideally, researchers validate maps by way of comparison with some independent data set – preferably ground data – collected for that specific purpose. Unfortunately, these data are expensive, and commonly end up being used for more urgent needs, like training classifiers and establishing empirical relationships. Specific strategies like cluster sampling can be used to increase the efficiency of field data collection, but, in general, these data contain less information per unit sampled than those from pure or stratified random procedures (Edwards *et al.*, 1998). Air photos and other higher-resolution brands of remote sensing are by far the most common source of validation information for large-area projects (Franklin and Wulder, 2003). For example, coarse-resolution AVHRR products are routinely validated with higher-resolution TM imagery (e.g., Fazakas and Nilsson, 1996; Scepan, 1999). IKONOS and Quickbird instruments could perform a similar function for ETM+. The ultimate solution could resemble a coordinated use of both field- and image-based validation methods. Clearly, more research is required.

V Linking information needs with remote sensing strategy

Ecosystems are a somewhat abstract concept, and there are competing viewpoints as to which elements are important to map for the purpose of science and management over large areas. Graetz (1990) suggested that the characteristics of ecosystems are determined by the primary trophic level – the vegetation – and that vegetation can therefore be taken as the functional equivalent of terrestrial ecosystems. Remote sensing scientists have been quick to adopt this viewpoint, since vegetative units are much simpler to map than the complex interplay of physical (soils, climate, topography) and biological (wildlife, vegetation, micro-organisms) agents that define the alternative viewpoint.

Unfortunately, many remote sensing products can be criticized for presenting an overly simplistic representation of vegetation, perhaps contributed to by historical limitations of satellite data and the ubiquitous use of classification as an information extraction technique. However, both of these factors have undergone recent change, with the growing number and availability of commercial and noncommercial satellites acquiring data with ever-increasing spatial, spectral, and temporal dimensions (Phinn, 1998). While these newfound choices have the potential to greatly enhance our ability to conduct ecological monitoring and management, they also present unique challenges surrounding the selection of appropriate data and techniques. The discussion of infomation-extraction strategies for use in large-area ecosystem management applications must therefore begin with a review of the remote sensing scene model, and how it relates to vegetation as a hierarchical, multiscale phenomenon.

1 Multiscale vegetation structure

Understanding the structure of complex, natural systems is a key challenge for all disciplines dealing with these phenomena (Marceau and Hay, 1999). Contemporary works in landscape ecology (e.g., Gardner et al., 2001; Turner et al., 2001) emphasize the interaction between vegetation stands distributed across the Earth's surface. This 'mosaic of patches' implies a certain conceptual model concerning the nature of vegetation, which can be articulated formally as complex systems theory. Complex systems theory describes the behaviour of ecological systems characterized by a large number of components interacting in a nonlinear way and exhibiting adaptive properties through time (Kay, 1991; Hay et al., 2002). An important characteristic of complex systems is that they intuitively take the form of a nested hierarchy, in that finer categorical divisions (leaf, canopy) are nested within broader ones (tree, stand). This hierarchical structure is employed by many classification systems in their attempt to organize vegetation by process rate, scale, or taxonomy (see summaries by J. Franklin and Woodcock, 1997, and S.E. Franklin, 2001).

Woodcock and Harward (1992) presented a hierarchical model that describes patterns of matter and energy flux in a forested scene that consists (in ascending order) of trees/gaps, stands, forest types, and scenes. Their model compares closely to Urban et al.'s (1987) process-based organization of vegetation into gaps, stands, cover type, provinces, and biomes. The stand (often referred to as a 'patch' in the landscape ecology literature) is defined as a contiguous area of similar species composition, plant cover, and plant size distribution (J. Franklin and Woodcock, 1997). Trees and gaps are nested within stands, which in turn are subsumed by larger landscape units or cover types, defined by Cousins (1993) as a complex of systems that form a recognizable entity. While there is some discussion regarding the scale of cover type units (e.g., Forman and Godron, 1986; Urban et al., 1987; Turner et al., 2001) they are generally considered to be on the order of 1000s of hectares, and correspond quite closely to the Level II classes of Anderson et al. (1976).

While differences between the various classification systems in use (spatial, taxonomic, process-based) can create considerable confusion, the understanding of vegetation as a complex system – and subsequent adoption of one or more hierarchies – is important to large-area habitat mapping projects for the following reasons:

1. they represent the foundation of communication between resource managers and remote sensing specialists;
2. they provide a framework for conducting multiscale mapping and modelling activities;
3. they provide a conceptual basis for linking ecological information to the remote sensing scene model and subsequent information extraction techniques.

2 The scene model

Strahler *et al*. (1986) described the remote sensing model as having three distinct components: the sensor, the atmosphere, and the scene. The scene model comprises the area of interest, which, in a forest, is composed of a forested portion of the Earth's surface viewed at a specific scale. For many applications, it is appropriate to consider the scene as a spatial arrangement of discrete two- or three-dimensional objects distributed on a background (Jupp *et al*., 1988; 1989). In real scenes, objects are formed by spectrally homogeneous pixels, and can take many different forms depending on scale. For example, a conifer forest scene could be modelled at a detailed scale as a series of two-dimensional objects composed of sunlit and shaded patches of forest and understory, or, at a broader scale, as a mosaic of structurally homogenous forest stands.

The relationship between the size of the objects and the spatial resolution of the scene follows one of two types: H-resolution or L-resolution (Strahler *et al*., 1986). The H-resolution case occurs when the pixel size of the scene is significantly smaller than the objects of investigation, while the L-resolution case occurs when pixels are larger than objects (Figure 2). This

designation is important, since it describes the fundamental relationship between the objects of interest and the spatial resolution of the image, which in turn governs the choice of subsequent information extraction techniques.

Generally speaking, H-resolution images are best suited for classification, since the objects of interest occur over areas larger than individual pixels. Depending on the specific structure of the scene, analysts can employ a wide variety of image processing techniques to extract the variables necessary for consistent discrimination, and may employ resampling (Franklin and McDermid, 1993) or segmentation (Woodcock and Harward, 1992) strategies to better define the objects of investigation. L-resolution scenes, on the other hand, are more suited to per-pixel routines such as vegetation indices (Satterwhite, 1984; Cohen, 1991), empirical (Moisen and Edwards, 1999; Cohen *et al*., 2002) or physical (Goel, 1988; Scarth and Phinn, 2000) models, and spectral mixture analysis routines (Peddle *et al*., 1999) that relate sub-pixel biophysical properties to multispectral reflectance measurements.

A critical characteristic of remote sensing scenes is the following: since natural systems are composed of objects in a multiscale hierarchy, a single image can be both H-resolution with respect to some types of information and L-resolution with respect to others. Following Woodcock and Harward's (1992) hierarchical forest scene model described earlier, a Landsat ETM+ image would be L-resolution at the tree/gap level, since each 30 m pixel consumes several tree/gap objects (top part of Figure 2). However, the same 30 m imagery would be considered H-resolution with respect to stands, which may cover 10s or 100s of hectares and consume many individual pixels (bottom part of Figure 2). As a result, the 'correct' information extraction strategy for ecosystem management can vary greatly, and depends jointly on (i) the scale of information desired, and (ii) the spatial resolution of the image used.
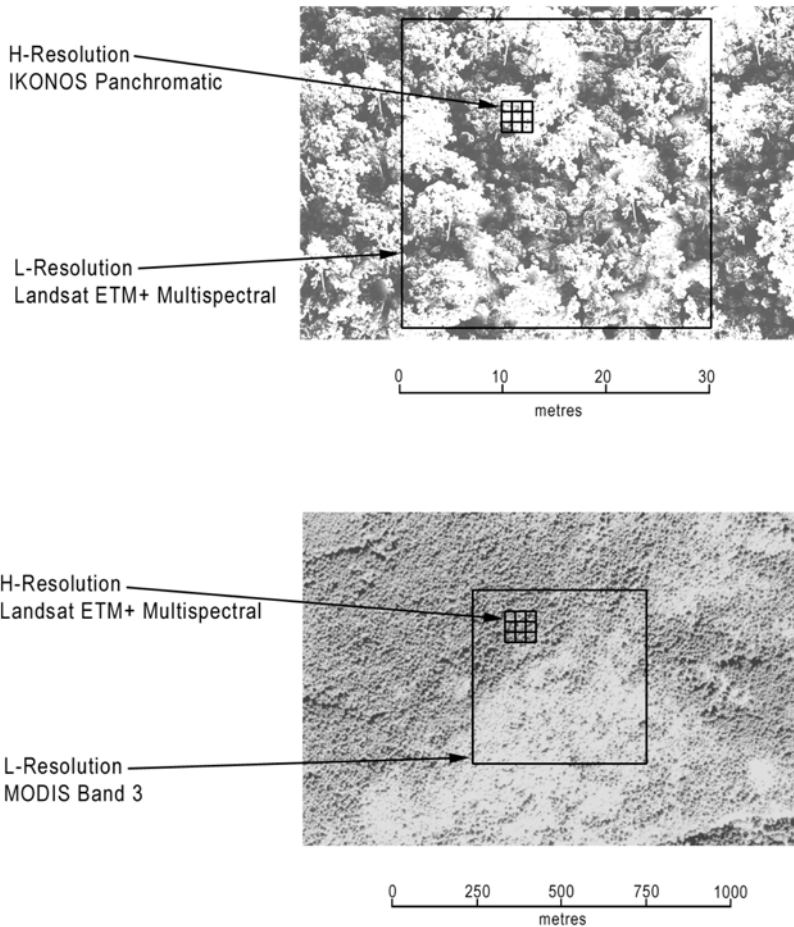
Figure 2 H- and L-resolution scene models for a forested scene. At the tree/gap level (top), Landsat ETM + multispectral pixels are L-resolution, while IKONOS panchromatic pixels are H-resolution. At the stand level (bottom) Landsat ETM + multispectral pixels are H-resolution, while MODIS band 3 pixels are L-resolution

3 A framework for application

Phinn *et al.* (2003) presented a framework for selecting the appropriate remote sensing data for environmental scientists. The process consists of the following six steps: (i) identify the information requirements for the project; (ii) organize the information needs in terms of an ecological hierarchy; (iii) conduct an exploratory analysis using existing digital data; (iv) identify the ideal remote sensing data, considering spatial, spectral, radiometric, and temporal dimensions; (v) select and apply a suitable set of information extraction techniques; and (vi) conduct a cost benefit analysis. This process can be visualized with the help of Figure 3: a hypothetical landscape that is to be the study area of a regional habitat-mapping project. By identifying various vegetation attributes as the required information products, we can adopt a multi scale hierarchy that organizes the scene in ascending scale as tree/gap, stand, and

Forest Type   **Stand**   **Tree/Gap**

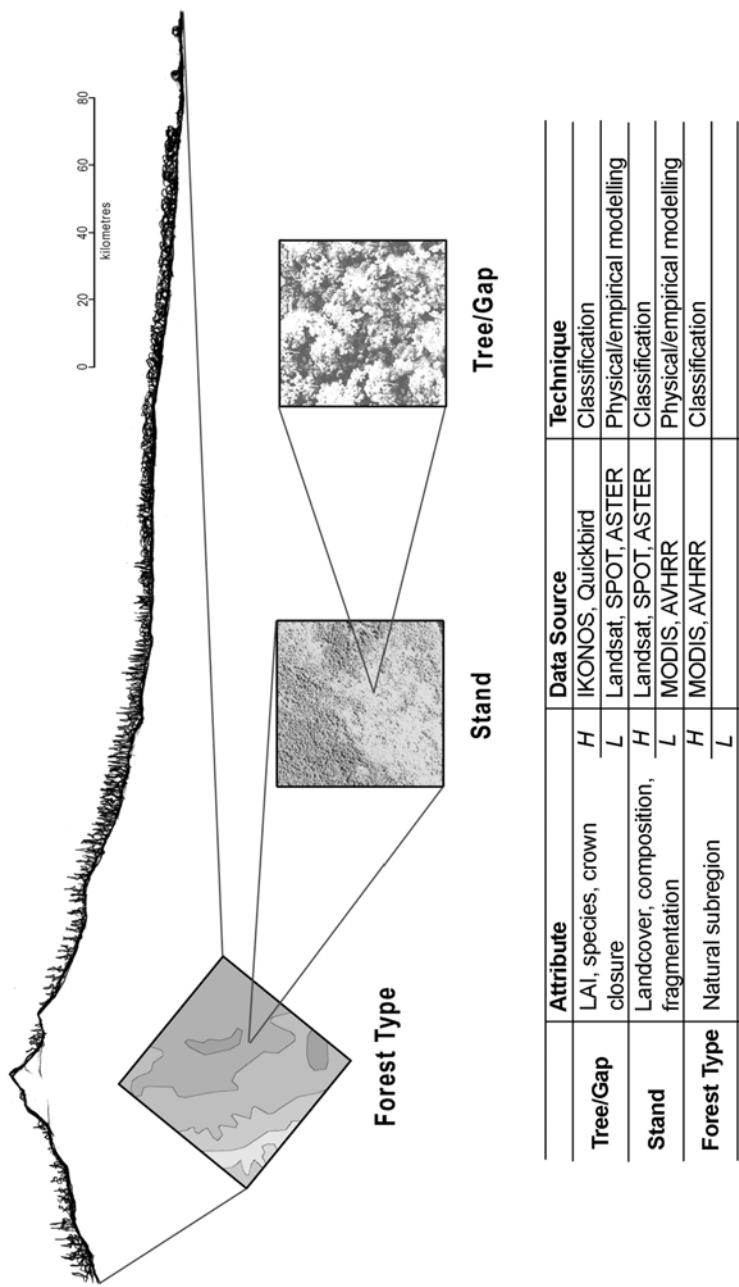|	Attribute		Data Source	Technique
Tree/Gap	LAI, species, crown closure	*H*	IKONOS, Quickbird	Classification
		L	Landsat, SPOT, ASTER	Physical/empirical modelling
Stand	Landcover, composition, fragmentation	*H*	Landsat, SPOT, ASTER	Classification
		L	MODIS, AVHRR	Physical/empirical modelling
Forest Type	Natural subregion	*H*	MODIS, AVHRR	Classification
		L		

Figure 3   A vegetation hierarchy is imposed on a theoretical landscape for the purpose of selecting the ideal remote sensing data and information extraction techniques

cover type. Specifications for the ideal remote sensing data can vary, depending on vegetation conditions, study area size, and available image processing techniques. Figure 3 offers H- and L- resolution suggestions at each level of the hierarchy. The choice of data should dictate – at least initially – the subsequent image processing techniques pursued: generally, classification for H-resolution data and physical or empirical modelling for L-resolution cases. Assessing the benefits of the resulting investment should take into account, among other things, the accuracy of the information products generated, the value of the resulting habitat maps, and the utility of the vegetation database for other resource management applications.

VI Summary and conclusions

A strong alliance is forming between remote sensing and ecology to address the challenge of large-area habitat mapping. However, the harmony of this multidisciplinary approach to science is hindered by miscommunication and the lack of common understanding. Pioneering work has demonstrated the promise of geospatial tools in crossdisciplinary work, but a tremendous amount of research yet remains. Image classification, per-pixel models, and spatial pattern analysis techniques are effective tools for extracting information, but scientists and resource managers require guidance for their effective application. A framework that combines hierarchy theory with elements of the remote scene model presents a mechanism for linking information needs with image processing technique, as well as a foundation for communication between ecologists and specialists in remote sensing. Future research should explore the integrated role of new remote sensing instruments and emerging technologies, develop techniques for constructing multiscale vegetation databases over large areas, and test the utility of these databases for supporting diverse environmental applications.

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