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Approaches for Monitoring Landscape Composition and Pattern Using Remote Sensing

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Introduction

For forest biodiversity assessment in Alberta, the scale of the element being targeted will determine whether data are best collected through field sampling or remote sensing. Genetic, population, and assemblage/community level diversity assessments will require terrestrial and aquatic field measurements. For detecting landscape level diversity and patterns of environmental variation, remote sensing is clearly a very practical method of collecting data (Davis and Dozier 1990; Stoms and Estes 1993; Naveh and Liebermann 1993) or at least a significant portion of the required data (Lillesand 1996; Nemani and Running 1996; Waring and Running 1998). For example, remotely sensed data can be used to classify vegetation structure and composition over large areas. The relationships between species distribution patterns and other remotely sensed landscape patterns can be developed through multivariate analyses and spatial statistics. Once relationships are established between ground and remotely sensed measures, comparing images at sequential time intervals can indicate important changes in the landscape pattern that are useful for monitoring biodiversity. This approach is not new or untested. However, within the biodiversity monitoring program objectives, careful consideration of a large number of issues must be addressed even in this simple design. Concerns range from image spatial resolution, to radiometric correction, to landscape patch dynamics, to standardized output format, and accuracy assessment. This careful consideration is intended to lead to the development and testing of *a remote sensing protocol* for biodiversity monitoring applications in Alberta.

Many questions require consideration before a remote sensing biodiversity monitoring protocol can be developed fully, tested, and implemented. For example:

- What remote sensing image data and methods should be used?
- What are the relationships between spatial scale and image resolution?
- What spatial resolutions are optimal for patch delineation and monitoring over time at a given scale?
- What level of georadiometric processing should be applied?
- Is there a standard image classification methodology?
- What classification system should be adopted and what relationship (if any) would the optimal system have with existing vegetation mapping systems?
- What field and GIS data are required?
- What is the definition of a patch (tree species composition, disturbance, productivity)?
- Can disturbance patches be mapped as accurately as less dynamic features?
- How will patch dynamics (persistence, change, etc.) be monitored spatially?
- What metrics are stable and can be validated in the wide range of forested landscapes that need to be considered?
- What are the investments in personnel and training that are required to support an emerging and evolving remote sensing protocol with multiple objectives?

This chapter is an attempt to begin to answer such questions and to define the framework within which remote sensing can contribute to the assessment of forest biodiversity in Alberta. A general presentation of digital remote sensing data characteristics, scale and spatial resolution precedes an interpretation of the characteristics and potential role of remote sensing systems in monitoring specific landscape-level elements of forest biodiversity, including some of those suggested by the Canadian Council of Forest Ministers (1997). A brief literature review of the relevant uses and methods of remote sensing in this context is provided. Currently available and proposed remote sensing systems are highlighted in terms of the data characteristics. A review of selected concepts from current ecological theory, of potential biodiversity elements and disturbance measures leads into a discussion of measures of fragmentation and other metrics useful for evaluating landscape level change. Some recent federal initiatives, such as the National Forest Inventory (NFI) and Earth Observation for Sustainable Development of Forests (EOSD), are introduced and briefly evaluated for possible synergism and consequences for the emerging AFBMP framework. Finally, the general format for a pilot study is recommended for implementation and future testing of remote sensing for gathering information on biodiversity elements of Alberta's forests.

Objectives

The main objective of this chapter is to provide an overview of the current capability of remote sensing technology to monitor aspects of biodiversity in Alberta, within the general biodiversity monitoring framework proposed by Schneider (1997). This assessment will enable a series of recommendations on possible configurations for a pilot study in Alberta and the development of a protocol or set of protocols that will encompass image acquisition, analysis, and interpretation issues. Specific objectives are to:

- Address technical issues, such as scale, data resolution, georadiometric corrections, image processing methods, integration with GIS;
- Review the literature for previous studies and examples of remote sensing in biodiversity monitoring;
- Illustrate the methods and algorithms used in those studies;
- Estimate the personnel, cost, scale and time required to perform landscape level monitoring using remote sensing;
- Summarize the practical and/or optimal ways to link to other biophysical and environmental monitoring programs;
- Recommend a one-year pilot study to be applied to one or more areas of Alberta.

Remote Sensing Perspective

Introduction

"*Any serious quantitative study of the landscape begins with some type of remote sensing; there is simply no other way to obtain consistent measurements across large areas*" (Waring and Running and Coughlan 1998: p.246). Aerial photographs have long been the default method of remote sensing in applied terrain studies (Townshend 1981). No doubt aerial photography will continue to play a major role in many such applications including forest inventory (Lowell and Edwards 1996). However, Glackin (1998) has identified a recent trend in the commercial development of small spaceborne remote sensing platforms with high spatial detail sensors and high repeat coverage. These suggest a more successful penetration of the traditional markets of aerial photography, including (or perhaps targeted at) terrestrial applications such as forest inventory. Particularly promising are the potential satellite remote sensing attributes created by new developments in sensor technology, computing, and related geographical technology (e.g., GPS).

Digital systems and digital image data appear to be the most likely foundation for future mapping and monitoring systems. In essence, the high cost of repeated and extensive aerial photographic surveys, widespread subjectivity in aerial photo interpretations, and general lack of radiometric calibration for aerial photograph analogues have led to an emphasis on the development of monitoring systems without these disadvantages. Furthermore, they can apply to any scale and any range of phenomena. The result has been the successful deployment and continued advances in remote sensing systems with the following characteristics:

1. Complete digital acquisition of data with known georadiometric error patterns;
2. Repeatable (time-series) and synoptic (spatially-explicit) coverage;
3. Multiple scientific methods of analysis, and;
4. An array of flexible and powerful output formats (that can easily be viewed as inputs to a following stage of analysis).

Various types of remote sensing systems have been designed with these features to obtain information about biophysical phenomena from a distance, using detectors manufactured to measure energy in different regions of the electromagnetic spectrum. Now widely available, these digital remote sensing systems capture emitted and reflected electromagnetic radiation appropriate for operational environmental applications in terrestrial ecosystems. Typically, radiation is measured in the optical/infrared, thermal infrared and microwave portions of the electromagnetic spectrum. Table 7.1 contains a summary listing of the main sensor/platform packages available. The list is dominated by *passive sensors* such as those deployed by the Landsat or SPOT satellite series, which detect naturally emitted (e.g., thermal) and reflected (e.g., visible, infrared) wavelengths from the earth's surface. Panchromatic sensors detect a single, wide band of visible to near-infrared light, whereas multispectral sensors can detect two or more bands. Hyperspectral sensors can be programmed to record many (100's) extremely narrow wavelength bands.

Table 7.1 Selected current remote sensing systems. Modified from Jensen (1996) and Sabins (1996)

REMOTE SENSOR SYSTEM	**RESOLUTION**									**Swath Width**
	Spectral							**Spatial**	**Temporal**	
	Blue	Green	Red	Near IR	Mid IR	Thermal IR	Micro wave	(meters)	(days)	(kms)
Aircraft										
Panchromatic film		0.5	------	0.7 um				Variable	Variable	
Color film	0.4	-------	------	0.7 um				Variable	Variable	
Color infrared film		0.5	------	0.9 um				Variable	Variable	
Daedalus DS-1268 scanner	1	1	2	2	2	2		Variable	Variable	
NASA Thermal IR Multispectral Scanner (TIMS)						6		Variable	Variable	
Compact Airborne Spectrographic Imager (CASI)	0.4	-------- 288 Programmable Bands	------	0.9um				Variable	Variable	Variable
Satellite										
NOAA-9 AVHRR LAC			1	1	1	2		1100	14.5/day	2700
NOAA - K,L,M			1	1	2	2		1100	14.5/day	
Landsat Multispectral Scanner (MSS)		1	1	2				79	16-18	185
Landsat Thematic Mapper (TM)	1	1	1	1	2			30	16	185
						1		120	16	185
SPOT HRV Multispectral		1	1	1				20	5-26	60
SPOT Panchromatic		0.53	------	0.73 um				10	5-26	60
SMS/GOES Series (east and west)		0.55	------	0.72 um		1		700	0.5/hr	
Indian IRS										
IRS-1A/B LISS I	1	1	1	1				72.5	22-24	148
IRS-1A/B LISS	1	1	1	1				36.3	22-24	146

II										
IRS-1A/B LISS		1	1	1				23.5	22-24	142
III					1			70.5	22-24	148
IRS-1C/D LISS-		1	1	1				25	24	142
III Multispectral					1			70	24	148
IRS-1C/D LISSIII Panchromatic		--------	------	-------				5	5-24	70
IRS-1C/D WiFS			1	1				188	24	774
European Remote Sensing Satellite (ERS-1)										
SAR for image/ wave mode		V V C-Band (5.3 GHz)					1	10-30	16-18	1
Scatterometer for wind mode							1	5000		500
Radar altimeter 13.8 GHz							1			
Along tract scanning radiometer (ATSR)		4 IR Bands (1.6, 3.7, 11, 12 um)						1000		
JERS-1 OPS		1	1	2	4			20	44	75
RadarSat		HH C-band (5.3 GHz)					1		1 - 6 days	
Standard Mode (range x azimuth resolution)								25 x 28		100
Wide 1 mode								48-30 x 28		165
Wide 2 mode								32-25 x 28		150
Fine resolution mode								11 x 9		45
ScanSAR (N) mode								50 x 50		305
ScanSAR (W) mode								100 x 100		510
Extended (H) mode								22-19 x 28		75
Extended (L) mode								63-28 x 28		170
Shuttle Imaging Radar							3	40	Variable	
EOS-AM-1 Advanced Spaceborne Thermal Emission and Reflectance Radiometer										
ASTER	0.5	-------- 3 bands	-----	0.9 um				15	Unknown	
ASTER				8.0 um	-----5 bands	12.0 um		90	Unknown	
ASTER				1.6 um	---- --6 bands	12.5?		30	Unknown	

Active sensors detect wavelengths returning to them that were originally supplied from the sensor system as a pulse or beam. The beam direction and polarization often can be specified to obtain optimal surface information. Examples of active sensors include synthetic aperture radar (SAR) (Sardar 1997) and light detection and ranging (lidar) systems (Lefsky et al. 1999). Radar has the advantage of being able to penetrate almost all atmospheric conditions, i.e., cloud, smoke, smog, fog, light rain and snow. Since radar energy can be detected regardless of light and atmospheric conditions, environmental conditions in winter and areas frequently covered by clouds can be monitored. In addition, active sensors can provide information on forest cover type (Ahern et al. 1993; Yatabe and Leckie 1995), burned areas (Ahern et al. 1993; Kasischke and French 1995) and vegetation structure (Hyppa and Hallikainen 1996; Wilson 1996; Naesset 1997). However, lidar and radar remote sensing applications continue to be two of the most active research areas within the earth observation field, with new sensors being developed and deployed in a variety of settings. Few operational examples of radar remote sensing in ecology have been reported (Waring et al. 1995) although the availability of Radarsat imagery in the last few years has generated a large number of new initiatives (e.g., Ahern et al. 1996; see the Special Geomatics in the Era of Radarsat issue of the *Canadian Journal of Remote Sensing* 1998, Volume 24, issues 3 and 4). The first satellite-borne lidar sensors are planned for launch in mid-2000 as part of NASA's Earth System Science Pathfinder program (Lefsky et al. 1999).

A list of recently launched and proposed (Table 7.2) remote sensing systems that can be used in a wide range of landscape applications, including mapping land use, urban expansion, geomorphology and soils, as well as monitoring biodiversity, shows the large number and diversity of future systems. Included in this table are the designed spatial and spectral resolutions important for detecting data at various scales for subsequent interpretation of underlying environmental phenomena. A new development of the next generation of satellites will be the provision of hyperspectral sensors from space (now currently only available from airborne systems). For instance, the Orbimage Orb View-4 Hyperspectral sensor scheduled for orbit in 2000 is being designed to resolve 200 bands of the spectrum (Table 7.2). An Australian satellite, ARIES, has similar hyperspectral capabilities and is also scheduled for launch in 2000. Another major change for future satellite systems is the provision of high spatial detail imagery that will approximate the level of detail available in aerial photographs at medium to large-scales. Virtually all of the planned visible and near infrared sensing systems will have spatial resolutions on the order of 1 m-4 m, compared to the existing (1999) complement of satellite sensors (e.g., IRS, Landsat, SPOT) which have spatial resolutions ranging from 5m to 30m.

Table 7.2. Selected Future and Recently Launched Satellite Remote Sensing Systems - Modified from Dechka (unpublished) and Wulder (1997)

REMOTE SENSOR SYSTEM	**EXPECTED LAUNCH DATE**	**RESOLUTION**			**SWATH WIDTH (kms)**
		Spectral		***Spatial***	
		Visible and IR Channels	Radar Channels	(meters)	
IKONOS 1	1999				
Multispectral		4		4	11
Panchromatic		1		1	11
Earth Watch QuickBird	1999				
Panchromatic				0.82	22
Multispectral				3.2	
Orbimage OrbView-3 Multispectral	1999	4		4	8
Orbimage OrbView-	2000	1		1	8

4Panchromatic					
Hyperspectral		200		8	8
India IRS-P5 Panchromatic	1999	1		2.5	70
LISS IV		7		6, 23.5	140
India IRS-P6 AWiFS	2000	3		80	
ARIES	2000				
Multispectral		32 + 32		30	15
Panchromatic		1		10	15
SPOT-5 HRV Multispectral		3		10	60
		1		20	60
Panchromatic		1		5	60
VI		4		1150	60
KVR-1000 Panchromatic		1		1.56	40
Tk-350 Camera Panchromatic		1		10	200-300
Landsat 7 TM Panchromatic	1999	1		15	185
Multispectral		6		30	185
Landsat 7 TM Thermal		1		60	185
EOS AM-2	2004				
LATI		N/A		N/A	
MISR		N/A		N/A	
MODIS		N/A		N/A	
EOS-PM1	2000				
MODIS Multispectral		36		250,500, 1000	
EOS-E01	1999				
ALI		1		10	
		5		30	
		542		30	
		1		250	
HRST HRST/COIS Multispectral	2000	210		30	
PIC Panchromatic		1		5	
EROS -A CCD Panchromatic		1		1.5	14
EROS -B1 CCD Panchromatic		1		0.82	20
EROS -B2 CCD Panchromatic	2000	1		0.82	20
EROS -B3 CCD Panchromatic	2000	1		0.82	20
EROS -B4 CCD	2001	1		0.82	20

Panchromatic					
EROS -B5 CCD Panchromatic	2001	1		0.82	20
EROS -B6 CCD Panchromatic	2002	1		0.82	20
Resource 21 A,B,C,D	1999/2000				
Multispectral		5		10,20	
Cirrus		1		100 +	
ADEOS-II GLI Multispectral	1999	34		250 - 1000	
KOMPSAT CDD	1999			10	
ENVISAT-1 ASAR	1999		1	30150	
ENVISAT-1 MERIS			15	300	
XSTAR	2001		10+1	20	
Radarsat 2 SAR	2001		1	Variable	
ALOS Panchromatic	2002	1		2.5	
Multispectral		4		10	
VSAR			1 SAR	10	
LightSAR	1999		4	1-100	
Space Shuttle	Varies		3	30	

Aerial and Satellite Remote Sensing

The features of available airborne and satellite systems useful for monitoring biodiversity at multiple spatial scales are complementary. A summary of the advantages and possible trade-offs in deploying sensors from aerial and satellite altitudes might include reference to mission flexibility, data characteristics, area coverage and ease of control of critical mission parameters. Satellite sensor data provide larger area coverage, have fewer problems with sensor attitude, and require fewer and simpler image geometric corrections than airborne sensor data. Satellite sensors also provide synoptic (i.e., same time interval, spatially-explicit) coverage and provide coverage of an area at regular intervals, which can be important for detecting change. However, greater ground detail can be collected by modern airborne sensors having very high spatial and spectral resolutions (discussed in more detail below) than by current or even planned next-generation satellite systems. And, the number and spectral resolution of the bands can be programmed more readily to meet the specific needs of the researcher or monitoring program. Aerial remote sensing mission planning is much more flexible (although often much more costly).

A brief review of relevant issues is provided in the following sections that are intended to lead to a clear understanding of the possible role(s) of remote sensing in biodiversity monitoring. Issues are addressed that might be prominent or lead to insights in the development of a remote sensing protocol or series of protocols for biodiversity monitoring in Alberta. The assumption is that a remote sensing biodiversity monitoring protocol could potentially include suggestions, guidance or recommended actions related to:

- image acquisitions (e.g., resolution)
- sensor package
- subsequent supporting ground data (e.g., field spectrometer, atmospheric soundings),

- image analysis and interpretation strategies (e.g., classification approach, including decision-rules),
- type and format of GIS input and output maps
- metadata
- quality and quantity of verification and accuracy assessment exercises

For a more complete introduction to remote sensing technology, analyses and applications, including aerial photography, see Lillesand and Keifer (1994) or Jensen (1996). On issues of scale and resolution, the book by Quattrochi and Goodchild (1997) provides a reasonable starting point. Information on georadiometric corrections has been summarized by Franklin and Giles (1995), and those issues and more are covered in the image processing book by Sanchez and Canton (1998) and numerous journal articles (e.g., O'Neill et al. 1995; Richter 1997; Itten and Meyer 1993; Robinove 1982). Classification accuracy assessment is covered by Stehman (1997) and a new book by Congalton and Green (1998). Cohen et al. (1996) recently provided an interesting perspective and reasonably complete review of image processing for forest applications in the U.S. Pacific Northwest.

Characteristics of Data Acquired by Remote Sensing

The wavelength intensity reaching the remote sensing system is reported as a digital number (DN) for a specific area related to the instantaneous field of view (IFOV) of that sensor system. This area is generally referred to as a picture element, or *pixel*. Each pixel represents information received from a specific ground unit area, and is therefore, by definition, the smallest unit of information that results from data acquisition. (Note: pixels are generally considered to be equivalent to the spatial resolution of the sensor system, but pixels are in fact a result of the digital sampling applied to the original analogue signals recorded by the sensor). Pixels are arranged in two-dimensional image arrays and in *n*-dimensional layers or bands or channels corresponding to the information detected in each of the sensor bands. The raw pixel bands, channels or image layers are ready for correction, analysis and interpretation. Because the data are digital, mathematical and statistical procedures can be done automatically with computer-based image processing software.

The first processing step is often the georadiometric correction of the raw imagery to obtain physical measurements of electromagnetic energy (as opposed to relative digital numbers, or DNs) that match an existing map or database in a specific projection system. In SAR image applications, the raw image data are often expressed as a slant-range DN, which must be corrected to the ground range backscattering coefficient (a physical property of the target), as part of a georadiometric correction procedure. In the optical/infrared portion of the spectrum, raw remote sensing measurements are observations of radiance. This measurement is a property of the environment under which the sensor system was deployed. At-sensor brightness or radiance, expressed in milliradians per pixel or unit area, may be converted to an arbitrary DN (perhaps 8-bit, ranging from 0-255) but this measure would include contributions from the atmosphere, the target, adjacent slope flux, and so on. However, the measurement that is most useful in ecology and forestry is *reflectance*, which is a property of the target alone. Therefore, one of the first and most important processing steps is to convert raw pixel DNs to a physically-based measurement of the target of interest with a geometric system of referencing attached to the image array.

An understanding of two fundamental aspects of remote sensing imagery – scale and resolution – is useful before such geocorrections are discussed further.

Image Resolution

Resolution is a quality of any remote sensing image and can be referred to as the ability of the sensor system to acquire image data with specific characteristics. There are four main categories of resolving power applicable to remote sensing systems (Jensen 1996):

- *Spectral resolution* is the number and dimension of specific wavelength intervals in the electromagnetic spectrum to which a sensor is sensitive. Particular intervals are optimal for uncovering certain biophysical information; for example, in the visible portion of the spectrum, observations in the red region of the spectrum can be related to the chlorophyll content of the target (leaves). Broad band sensors, such as Landsat TM, are designed to detect radiance across a 50 nm or 100 nm interval, usually not overlapping. High spectral resolution sensors might be designed to detect very narrow intervals, perhaps 2 nm to 4 nm wide, around specific absorption features such as the chlorophyll a absorption interval.

- *Spatial resolution* is the smallest separation between two objects that can be distinguished by the sensor. A remote sensor at higher spatial resolution can detect smaller objects; but as mentioned previously, the spatial detail in any given image is a function of the instantaneous field of view (IFOV) of the sensor. Historically, spatial resolution from polar-orbiting terrestrial satellites has been on the order of 20 m to 1000m or more; recent advances (and military declassification) in sensor technology as well as the lower orbits selected for new platforms, mean that future satellite sensor spatial resolution may approach 1 m or less.

- *Temporal resolution* is the image frequency of a particular area recorded by the sensor. The recorded frequency of an image determines the type of environmental change detected by the sensor and the rates of change that can be estimated. Many new satellites (in the past 10 yrs) and most future satellites could increase revisit capabilities with programmable sensors that can look to one or other side of the nominal flight path. This has given rise to consideration of angular reflectance patterns (or polarimetric) signatures that could be considered a different kind of resolution altogether.

- *Radiometric resolution* is the sensitivity of the detector to differences in the signal strength of wavelengths from the target. Greater radiometric resolution allows smaller differences in radiation signals to be discriminated. This resolution is analogous to film speed in the analogue photographic systems. Colour changes that seem obvious in aerial photographs are not readily apparent in some digital imagery because of the large differences in radiometric resolution; colour aerial photography, for example, can theoretically provide many times the radiometric resolution of the Landsat TM satellite sensors. A reflectance change of a few percent can cause a dramatic change in colour visible to the eye and recorded on colour film (say, from green needles to red immediately following spruce budworm defoliation of conifers). However, those reflectance differences in the green and red portion of the spectrum recorded by satellite sensors hundreds of kilometres above the target would be minimal.

There are certain trade-offs in considering the resolving power of remote sensing systems from aerial or satellite platforms. For example, an increase in the number of bands is often accompanied by a decrease in the spatial detail (spatial resolution). To acquire more or narrower bands the sensor must view an area on the ground for a longer period of time, and therefore the size of the area viewed increases. If the radiometric resolution is increased (so that smaller differences in radiance can be detected), the spatial detail or number of bands or narrowness of the bands, or all three, must be reduced.

In aerial remote sensing, trade-offs in flight altitude, speed of the plane, and data rates for both scanning and recording result in constraints on the range of spatial detail that can be acquired in any application.

Many satellite systems provide a limited range of options in spatial and spectral resolution (Table 7.1); users must match the appropriate data acquisition parameters to the application at hand, often by selecting imagery from different satellites or a combination of satellites and aerial sensors for multiple mapping purposes on the same area of land. For example, if the objective is to map leaf area index within forest stands it would be possible, though perhaps not optimal, to acquire and process very high spatial resolution airborne imagery with individual trees visible. The approach would be to build the LAI estimate for a stand or given parcel of land from individual tree estimates. A completely different yet complementary strategy would be to acquire satellite imagery at a coarser spatial resolution and attempt to estimate LAI for larger parcels of the stand, then aggregate or segment the image. Although the methods would almost certainly become more complex, using aerial and satellite data in combination may provide results which are more accurate than relying on only a single image source.

Three different image resolutions are illustrated in Figure 7.1 using data acquired from the high (space) altitude Landsat Thematic Mapper satellite, the medium altitude Compact Airborne Spectrographic Imager, and the low altitude Multispectral Video airborne system. At the level of the satellite image, broad patterns in vegetation communities and abiotic/biotic/cultural features are clearly visible. Less clear are the variations within these groupings. In forested areas, for example, differences in dominant species and in productivity can be discerned through careful analysis of the relationships between cover and geomorphology. As an illustration, alluvial fans in this area tend to be good sites for deciduous cover, appearing a brighter pink in the false colour image. As the spatial resolution increases, the information content increases, but the area covered decreases. At the highest spatial detail (25 cm spatial resolution with the digital video system) individual trees are seen as discrete objects with clear separation from surrounding features; but only a tiny fraction of the area covered in the coarser resolution imagery can be reasonably mapped with this level of detail. This multiple resolution approach can yield a powerful data set that can be *scaled* from ground data to one image or areal extent to the next.

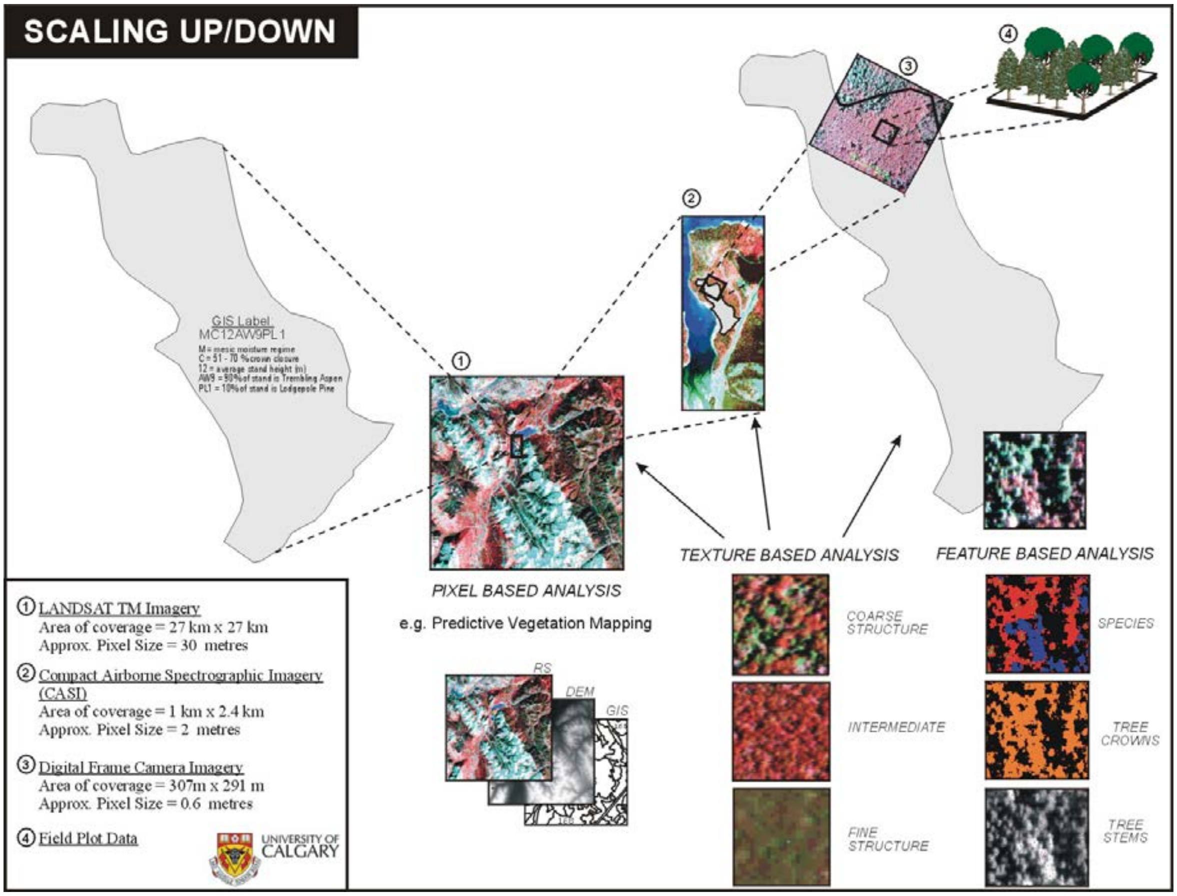


Figure 7.1 Scaling up/down with multiple resolution imagery

Relating Resolution and Scale

Scale is a pervasive concept in any ecological monitoring program and has a direct spatial implication in remote sensing. Scale is related to spatial resolution but is not an equivalent concept. Where resolution refers to the spatial detail in the imagery that might be used for detection, mapping, or study, scale refers to the area over which a pattern or process can be detected, mapped or studied. (Note: by convention, small-scale refers to large area coverage, and large-scale refers to small area coverage).

However, one simple way in which to relate scale and image detail is to categorize levels of *image spatial resolution*, which can be described based on the scale at which environmental phenomena can be *optimally* identified or estimated:

- *Low resolution imagery* – Optimal applications are in study of phenomena that can vary over 100's or 1000's of metres (small-scale) and could be supported with GOES, NOAA AVHRR and Landsat imagery. Examples of the use of this type of imagery includes mapping objectives at a small-scale: forest cover by broad community type (coniferous, deciduous, mixedwood); abiotic/biotic characteristics.

- *Medium resolution imagery* – Optimal applications are in study of phenomena that can vary over 10's of metres (medium-scale) and could be supported with imagery from Landsat, SPOT, IRS and Shuttle platforms, and by aerial sensors. Examples of the use of this type of imagery might include mapping objectives at the medium-scale: patch level characteristics and dynamics; tree species; crown diameters; tree density; the number of stems; stand-level LAI.

- *High resolution imagery* – Optimal applications are in study of phenomena that can vary over scales of centimeters to metres (large-scale) and are currently only supported by aerial remote sensing platforms and very specific applications of coarse resolution satellite imagery (e.g., TM unmixing studies). Examples of the use of this type of imagery might include mapping objectives such as individual trees and other discrete ground objects (understory assemblages); forest structure; forest cover (crown diameters, closure); LAI; understory composition or rare species detection. In the future it is expected that satellite spatial resolution will approach the level of detail required to support these and other such applications.

Of course, the data source is only one of several variables that must be considered in any monitoring application at any particular scale (Wulder 1998a). For instance, even if satellite imagery were available now at 1 m spatial resolution, the radiometric resolution (dynamic range) of the data may not be appropriate for some applications compared to the corresponding aerial sensor capability. Earlier experience in the late 1980's showed that the new SPOT HRV sensors had such a low dynamic range compared to Landsat TM sensor data, that the coarser resolution Landsat TM sensors were preferred in most forest defoliation studies (Franklin and Raske 1994). In addition, the optimal method for the identification of phenomena at a particular scale may not be the most accurate method possible. The best choice of methods and remote sensing data is a function of the scale and geographic extent of the project, personnel (e.g., technical training), and cost (data acquisition, data storage requirements, time for analysis, and so on).

Georadiometric Data Correction

The raw pixel or image data obtained from remote sensing systems must be processed in preparation for further analyses and interpretation. Radiometric and geometric corrections are performed to remove sensor-based and environmental-based errors. Geometric corrections can be relative or absolute; the availability of GPS has rendered subpixel geometric corrections tractable, and the ready availability of high quality DEMs has provided a foundation for orthorectification of satellite and aerial imagery, at least at the resolution of the DEM (usually, a medium-scale such as 1:20,000).

Radiometric corrections typically involve adjustments to the pixel value to convert radiance to reflectance using atmosphere and illumination models. The simplest image correction – apart from doing nothing – is to relate image information to pseudo-invariant reflectors, such as deep, dark lakes, gravel pits, or asphalt/rooftops (Teillet and Fedosejevs 1995). These objects should have low or minimally varying reflectance patterns over time, which can be used to adjust for atmospherically induced variance in other parts of the image. Incident light sensors and field deployed calibration targets are an indispensable data source for more complex atmospheric and illumination corrections. Two other sources of radiometric error, caused by topography and bi-directional reflectance properties are more difficult to address and require substantial ancillary information (such as coincident field observations or complex model outputs). SAR image calibration and correction is more complex and requires calibration target deployment (Waring et al. 1995).

In general, however, the radiometric corrections that would be appropriate in a biodiversity monitoring program that would rely heavily on image classification (see below), should not be expected to exceed current capabilities. In classification studies it is certainly possible, but not typical, to acquire absolute reflectance spectra of individual components of the ecosystem in order to characterize patch conditions adequately and other likely biophysical parameters of the targets. However, Cohen et al. (1998) found that in clearcut mapping over the 1970's to 1990's using Landsat data, there was no need to perform any radiometric calibration. The differences in spectral response recorded by the Landsat satellites over forest and clearcut areas were far greater than any differences observed due to atmospheric or illumination differences. The classifier was robust enough to overcome the uncorrected radiometric noise. Wolter et al. (1995) applied simple image calibrations in their multitemporal Landsat TM classification of forests in the northern Lake States region, and reported classification accuracies exceeding 83%. Earlier work (Wilson et al. 1994) with coarser resolution (spatially and spectrally) Landsat MSS imagery in the boreal forest region showed a similar pattern of reasonable classification accuracy (greater than approximately 75%) following relatively simple image georadiometric processing.

A larger scale project now being planned (Ahern et al. 1998; Shaffer 1996, 1997) to produce high quality, multi-resolution, multi-temporal global data sets of forest cover and attributes, called Global Observation of Forest Cover (GOFC), contains three different 'levels' of products based on raw, corrected and derived (classified) imagery. Existing methods of radiometric processing are considered sufficient for the general applications of such data, and users with more detailed needs can develop products from these three levels for specific applications. For example, in studies of high relief terrain with different (more detailed) mapping objectives, it has clearly been demonstrated that more complex radiometric and atmospheric adjustments are crucial to classification and parameter estimation accuracy (e.g., Itten and Meier 1993). Such corrections are now much more commonly available in commercial image processing systems (e.g., a simplified version of the Richter (1997) atmospheric model is a separate module within the PCI Easi/Pace system) and are not difficult, costly or overly complex to apply (Franklin and Giles 1995). Although georadiometric correction improvements are always possible and even inevitable, existing methods appear able to generate the required accuracy to permit the mapping applications to succeed and satisfy a wide range of ecological monitoring objectives.

Image Data Processing

Image data can be processed pixel-by-pixel using traditional image processing approaches that have been tested and applied in a wide variety of applications. One example of a per-pixel image processing approach is to compute spectral ratios or indices, such as the normalized-difference-vegetation-index (NDVI), which is derived from the red (R) and near infrared (NIR) bands of a multispectral image:

$$NDVI = (NIR - R)/(NIR + R).$$

Initially developed as a measure of green leaf biomass, NDVI statistics have been used in classifications and in estimation of biophysical properties of trees and canopies (Wulder 1998a). Since green leaves differentially reflect infrared light (from cell structures and water) and absorb red light (through photosynthesis), the NDVI is related to leaf area to the extent that leaf area is related to absorbed photosynthetically active radiation (PAR). Multispectral ratios such as the NDVI, and transformations such as the Tasselled Cap (brightness/greenness/wetness), are ideal in monitoring programs because they reduce the variance in a remote sensing data to a few, simple dimensions that can be interpreted readily in terms of the landscape pattern. For example, one reasonably consistent finding in various forest mortality studies (e.g., Collins and Woodcock 1996, Franklin et al. 1995), and clearcut mapping (Cohen et al. 1998) is that the shorter wavelength reflectance tends to increase and longer wavelength reflectance tends to decrease with decreasing amounts of vegetation. Such changes are readily summarized in brightness/greenness/wetness measures. This type of pixel-by-pixel image analysis - for example, to produce indices as input to regressions or classifications - has been the source of many of the advances in automated processing of image data in the past, and will likely continue to form one of the most powerful methods of interpretation in multispectral remote sensing in the near future (Waring and Running 1998).

The per-pixel approach often implies the development of *spectal signatures*, which are typically summary statistics of individual bands and transformations such as NDVI acquired over relatively homogeneous areas. However, imagery are multifaceted and multidimensional in feature-space (i.e., similar to aerial photographs, interpretation can be based on more than the tone of a specific object or area, but can include texture, pattern, shape and so on). By processing the multispectral information inherent to pixels together with spatial discriminators inherent to imagery, additional information can be derived by automated methods. As high spatial detail imagery and continued improvements in computing power become more widely available, a trend away from pixel-by-pixel (or per-pixel) processing can be identified in the computer image understanding literature (e.g., Guindon 1997) and in specific applications in remote sensing (e.g., St. Onge and Cavayas 1997; Brunizquel-Pinel and Gastuellu-Etchegory 1998; Gerylo et al. 1998).

Frohn (1998) has suggested that a new perspective on the use of remote sensing may be emerging through the notion of a *spatial signature*; although he was referring to landscape ecology applications, such as the use of metrics to summarize the spatial structure, the idea can be used to extend the application of spectral signatures to encompass spatial variability in remote sensing imagery this is a lengthy sentence. *Texels* (texture elements) are data derived from images that capture the spatial variation of pixels; that is, the spatial variation of tones or other types of pixel information. Texture has been related to successional patterns in vegetation communities (Jakubauskas 1997), and has been shown to be more strongly associated with vegetation structure than the original spectral response in several studies, especially when using high spatial detail imagery (e.g., Wilson 1996; Wulder et al. 1996). *Mixels* (mixture elements) are the component spectral signatures that contribute to the overall spectral signature recorded for a pixel (Peddle 1997). Each pixel is composed of multiple bands of pure spectral signatures obtained from various objects on the ground. Pixel decomposition or spectral unmixing can identify the spectral signatures belonging to particular objects, if there are a sufficient number of spectral bands and if the ground objects have known unique spectral signatures (perhaps through field spectrometry or a spectral library). *Fexels* (feature elements) are object-based data that reveal the spatial dimensions and spatial relationships of ground components. The first step to obtaining fexels is to identify and mark pixels with object-specific spectral signatures. The marked pixels are then used as seeds to grow objects using algorithms that recognize the object boundaries (Gerylo et al. 1998).

Remote sensing data can be analyzed with reference to existing data, and these existing data are often contained in geographical information systems (Figure 7.2). In general, the image data can be processed such that the GIS data are used to guide the analysis; in the example shown in Figure 7.2, the choice of equation to predict LAI from multispectral reflectance depends on the forest stand typing in the GIS. However, GIS data can be considered a source of information for use with the remote sensing image in classification (see section on improving classification accuracy, below). This step is shown in the centre panel of Figure 7.2 where the GIS data and the remote sensing data are included in the classifier decision rule together. And finally, most remote sensing information will ultimately be used to update or augment an existing GIS database; clearly the integration of remote sensing products into a GIS after the image processing is completed must be carefully planned. Some consideration of the format and metadata that might be required in this task is an important focus in the discussion of image extraction and processing strategies, and in the implementation of recursive procedures for remote sensing.

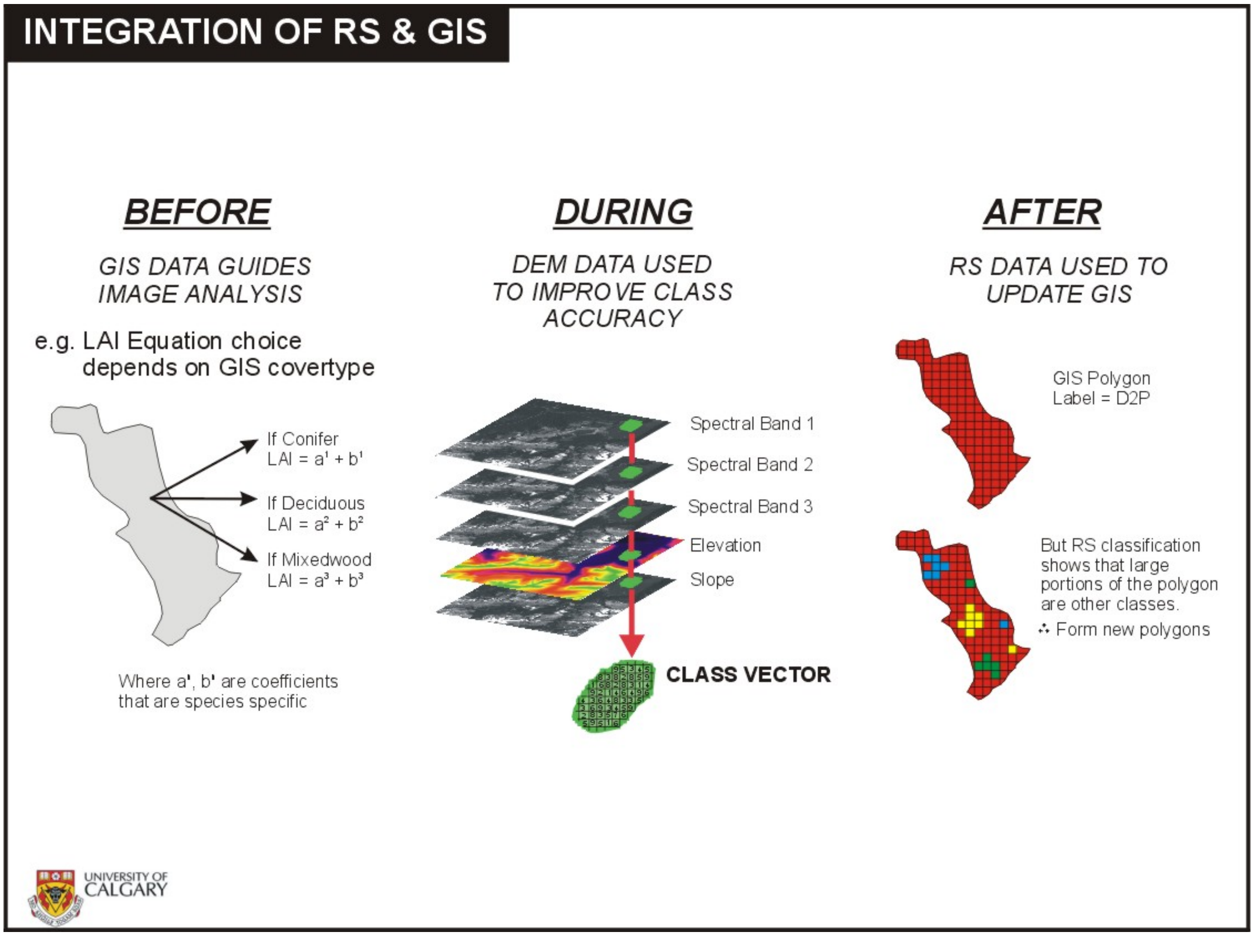


Figure 7.2 Integration of remote sensing and GIS

He et al. (1998: p.1072) provides an illustration of a method that integrates several data sources for assessing forest composition across large, heterogeneous landscapes (in Wisconsin). They derived a probabilistic algorithm to assign information from a point coverage (forest inventory sampling points) and a polygon coverage (ecoregion boundaries) to a raster map (satellite land cover classification). *"The satellite map captures the occurrence and patch structure of canopy dominants…The inventory data provide important secondary information on age class and associated species…In this way we derived new maps of tree species distribution and stand age reflecting differences at the ecoregion scale…These maps can be used in assessing forest patterns across regional landscapes, and as input data in models to examine forest landscape change over time."* Their study emphasizes the importance and value of using existing data with remote sensing imagery in certain applications (such as those requiring stand age estimates); although concerns over data uncertainty, error propagation and scale remain outstanding (Hunsaker et al. 1999).

Extracting Forest Biodiversity Information from Remotely Sensed Data

Continuous variable estimation and image classification are the dominant information extraction methods in remote sensing and are the likely strategies that will yield input variables to biodiversity assessment and monitoring programs in the near future. Continuous variable estimation in remote sensing is usually accomplished through an empirical search for relationships. Typically these relationships are sought through regression, such that the measured variable (reflectance) can be used to predict a biophysical variable (such as canopy closure or volume) with known error and statistical significance (Gemmell 1995, 1998; Trotter et al. 1997). Often the development of regression equations follows a classification, where the classes are used to stratify the landscape and reduce the variance to an acceptable degree that can be modelled (Franklin et al. 1997a, 1997b). In this instance, as in classification and change detection, the results are largely dependent on the quality and comprehensiveness of the input training data (Salvador and Pons 1998).

Image classification, in particular, can be considered a standard methodology in remote sensing and has the potential to be distilled into a protocol that can be extended spatially and temporally within an ecological monitoring program (Lillesand 1996). In any image classification project such a protocol would be based on several simple steps (Figures 7.3 and 7.4):

1. The development of a classification system comprised of individual and hierarchical classes that are exhaustive and mutually exclusive across the landscape;
2. The derivation and implementation of methods and algorithms that can be applied with understandable error patterns and identified uncertainty in decision-making; and
3. The application of a statistically sound accuracy assessment and validation of mapping products.

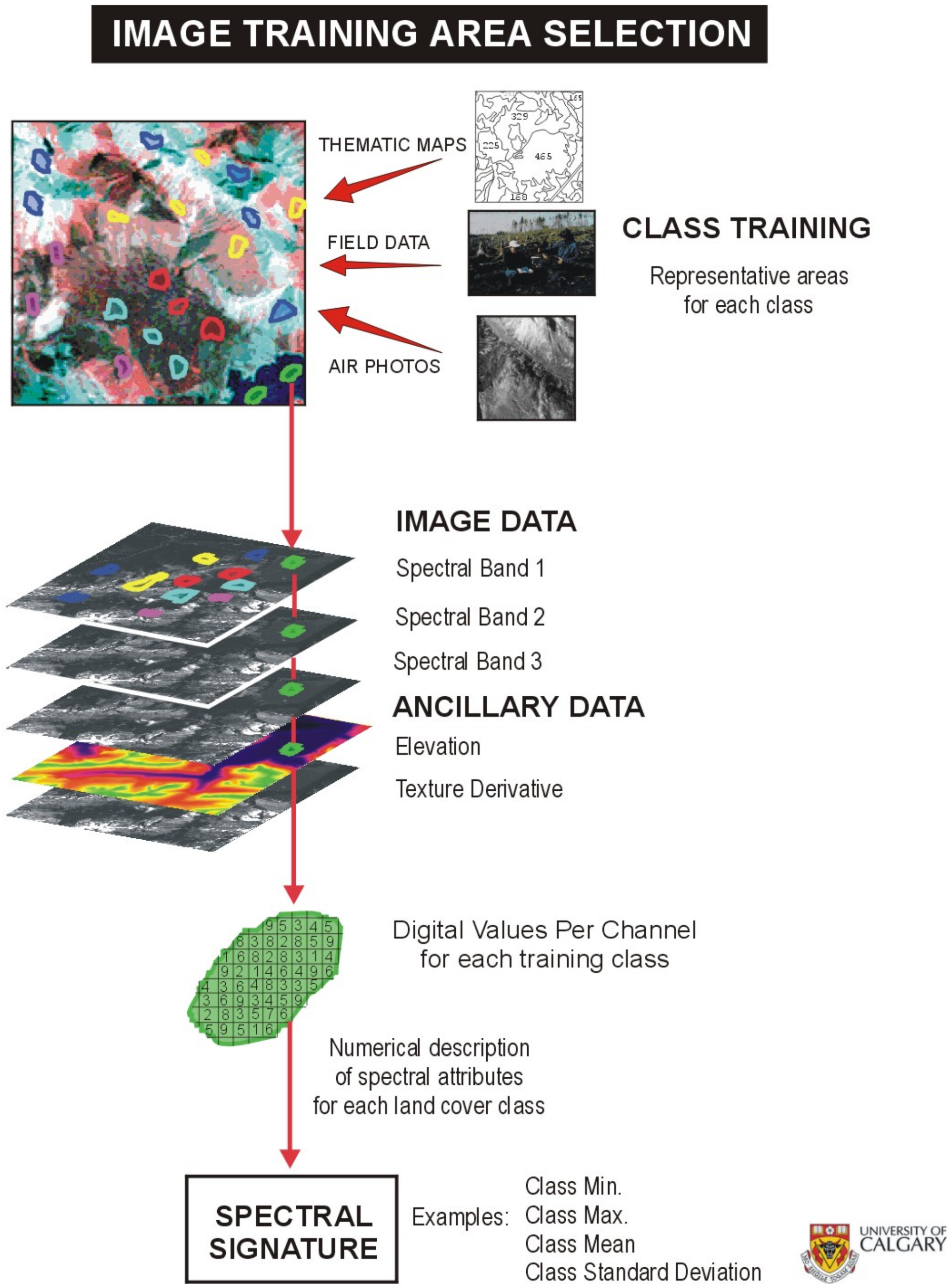
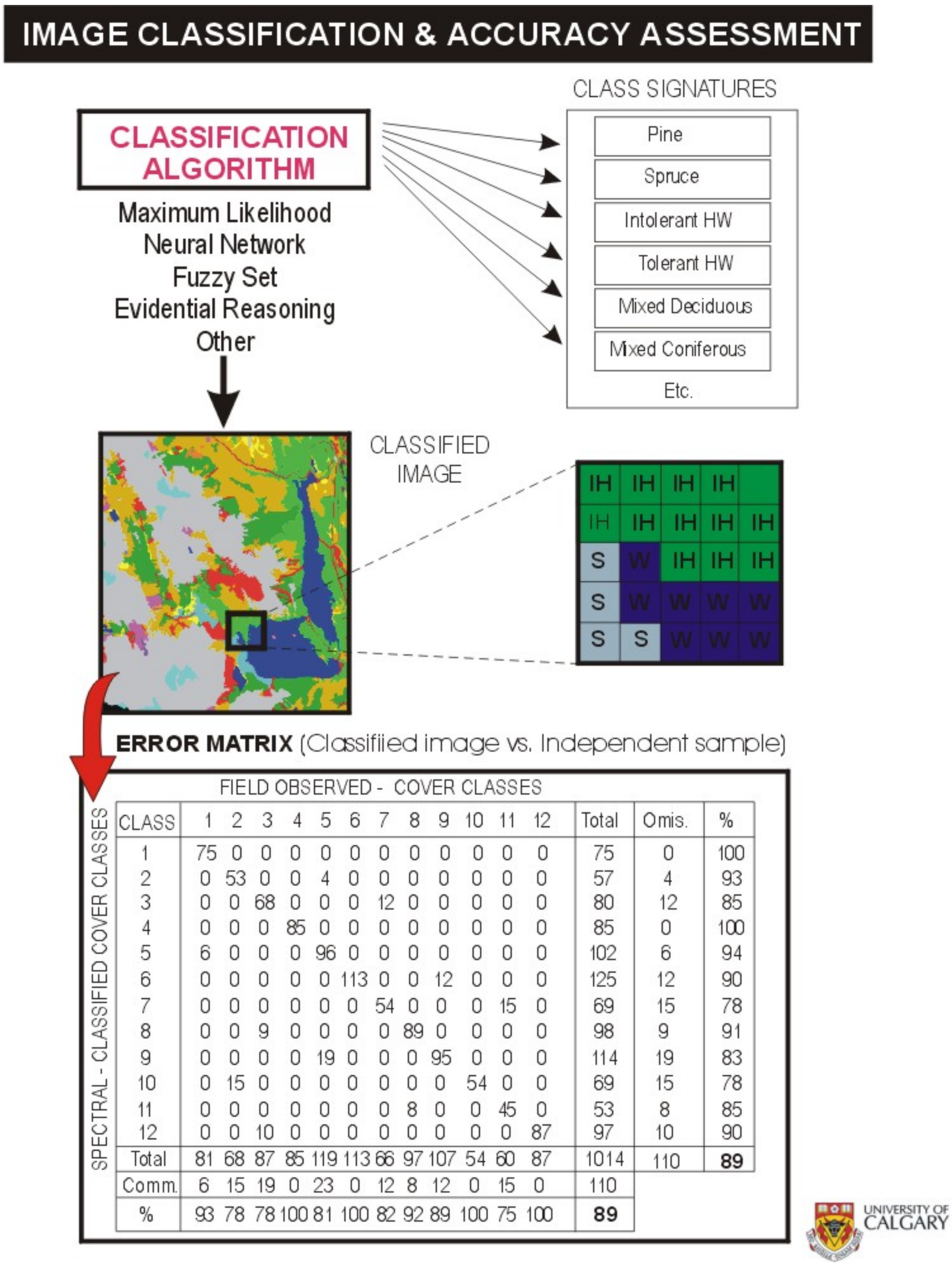


Figure 7.3 Image training area selection

There are numerous ways to improve classification accuracy and all should be considered depending on the expected results and the variability of the classes that must be mapped. A few options are essentially ‘no-cost’, perhaps involving only a choice of algorithms (Foody 1996; Peddle 1995). Recent algorithm development efforts have resulted in improved classifiers that are less sensitive to deviations from statistical assumptions (such as the assumption of input data normality and multicolinearity), and these options are increasingly available in commercial image processing systems.



CLASS	1	2	3	4	5	6	7	8	9	10	11	12	Total	Omis.	%
1	75	0	0	0	0	0	0	0	0	0	0	0	75	0	100
2	0	53	0	0	4	0	0	0	0	0	0	0	57	4	93
3	0	0	68	0	0	0	12	0	0	0	0	0	80	12	85
4	0	0	0	85	0	0	0	0	0	0	0	0	85	0	100
5	6	0	0	0	96	0	0	0	0	0	0	0	102	6	94
6	0	0	0	0	0	113	0	0	12	0	0	0	125	12	90
7	0	0	0	0	0	0	54	0	0	0	15	0	69	15	78
8	0	0	9	0	0	0	0	89	0	0	0	0	98	9	91
9	0	0	0	0	19	0	0	0	95	0	0	0	114	19	83
10	0	15	0	0	0	0	0	0	0	54	0	0	69	15	78
11	0	0	0	0	0	0	0	8	0	0	45	0	53	8	85
12	0	0	10	0	0	0	0	0	0	0	0	87	97	10	90
Total	81	68	87	85	119	113	66	97	107	54	60	87	1014	110	**89**
Comm.	6	15	19	0	23	0	12	8	12	0	15	0	110		
%	93	78	78	100	81	100	82	92	89	100	75	100	**89**		

Figure 7.4 Image classification and accuracy assessment

One of the most obvious ways to obtain classification accuracy improvements is to deploy and use improved aerial or satellite sensors such as those described in Tables 7.1 and 7.2. For example, if the mapping task was aimed at smaller wetlands rather than details within broad landcover types, perhaps the SPOT satellite with fewer bands but greater spatial resolution would provide higher accuracy over the Landsat TM sensor (Franklin 1994). Multiple observations by the same satellite or another sensor system could be used to detect phenological changes of vegetation (Wolter et al. 1995). A combination of SAR and optical/infrared data can be used to increase discrimination (Waring et al. 1995). Another approach to improved classification results, is to combine remote sensing imagery with ancillary data, perhaps derived from a GIS (as in the first part of Figure 7.2), and in areas of significant relief, a DEM (Franklin

1992). And finally, some combination of pixel, texel and mixel processing can sometimes be used to generate more accurate classifications (e.g., Gerylo et al. 1998).

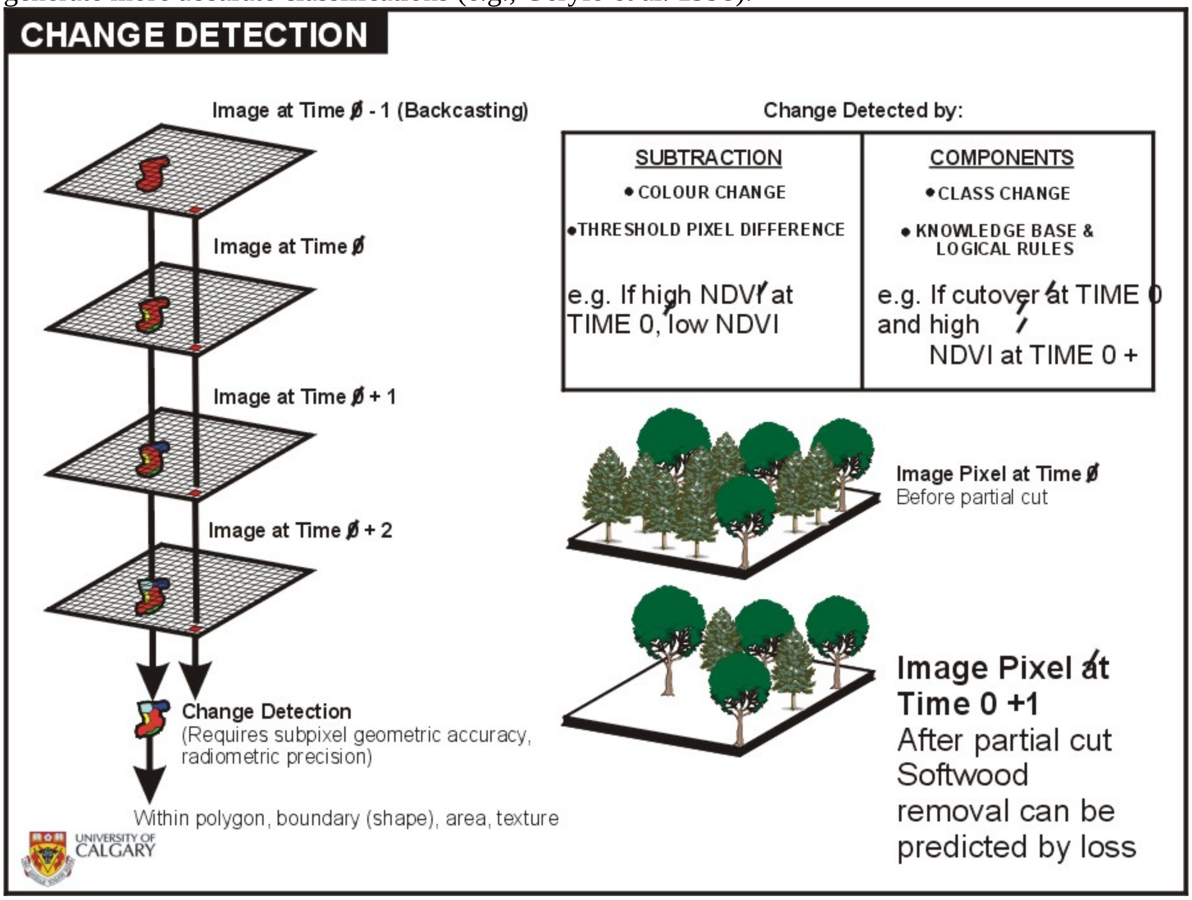


Figure 7.5 Change detection

One final aspect of remote sensing information should be addressed: image change detection (see Figure 7.5). A series of images acquired over time with radiometric and geometric fidelity can be subjected to trend analysis and differencing to identify anomalies and confirm patterns. This can be accomplished using relatively simple image pixel-to-pixel analysis (Singh 1989; Collins and Woodcock 1996; Franklin et al. 1999), or can be generalized to GIS-based structures such as forest stand polygons. Changes can be monitored within such boundaries and the accuracy of classifications over time can be evaluated (Congalton and Brennan 1998). Numerous studies have shown that detection of change in forest cover is possible (Hame et al. 1998), but that change detection methods must be adapted to detect optimally the type of change that has occurred in the landscape (Olsson 1994; Adams et al. 1995; Varjo 1996; Cohen et al. 1998).

Ecological Perspective

Biodiversity Elements, Patches and Mapping

As stated in the introduction of this chapter, elements of biodiversity are measurable at multiple scales of biological organization including genetic, population, ecosystem/community (Boyle 1991) and regional landscape (Noss 1990). In relation to the use of remote sensing, our focus is on those elements of biodiversity that can be observed as patterns within the regional landscape level of biological organization. Ecosystems or land covers that comprise the landscape are generally termed landscape elements or patches (Forman 1995). Depending on scale, a patch is a more or less homogeneous component that differs in some measurable way from neighboring patches (McGarigal and Marks 1995). Essential to functions of ecological systems (Turner 1989; Urban et al. 1987), *patch diversity* should be monitored as part of an overall strategy to conserve biodiversity (Farr 1998).

The phenomenon under consideration dictates whether a patch is defined from the geological substrate, the vegetation structure or productivity of the landscape area (McGarigal and Marks 1994). How patches are defined, in turn, sets the patterns of landscape that are detected. For instance, although there may be some biophysical relationship, patches based on vegetation class are likely to be of different size, shape and spatial arrangement than patches based on soil type. Some of the 'biodiversity' elements used to define patches are presented in Table 7.3. These elements are presented here to illustrate the range of biophysical attributes that can be remotely sensed and to attempt to show the diversity in landscape interpretations that could result following patch definition based on these or other elements. For example, a broad distinction is made between patches defined on the basis of directly measurable conditions, such as cover and structure, and patches defined on the basis of modeled processes, such as photosynthesis and vegetation stress. Landscape patches defined on the basis of structural estimates of density and canopy closure might differ considerably from patches for that same landscape defined on the basis of NPP or LAI.

Table 7.3 Examples of remote sensing biophysical attributes and models

Biodiversity Element	Models	Reference
Forest Cover	Spectral reflectance and classification	Franklin 1992; 1994
Plant Species Composition		
Dominant Canopy Species	Spectral reflectance and classification	Franklin 1992; 1994
Common Understory Species	Spectral reflectance, classification, and pixel unmixing	Ghitter et al 1995; Peddle et al 1996
Vegetation Structure		
Stand Density	Geometric optical modeling	Woodcock et al 1997
Stand Height	Correlation; lidar system	Wilson, B. 1996; Hyyppa and Hallikainen 1996; Naesset 1997; Lefsky et al 1999
Canopy Closure	Classification, correlation and unmixing	Gerylo et al 1998
Canopy Gaps	Classification	Milton et al 1997
Seral Stage	Classification	Jakubauskas 1996; Jakubauskas and Price 1997
Photosynthesis and Related Processes		
Intercepted Photosynthetically Active Radiation (IPAR)	Directly related to NDVI, but constrained by freezing temperatures, soil drought, and high vapor pressure deficits	Peterson 1997
Leaf Area Index	Directly related to NDVI, season dependent; improved with mixel	Gholz et al 1997; Peddle et al 1996

	data.	
Vegetative Biomass	Related to vegetation indices, improved with mixel data.	Peddle et al 1996.
% Vegetative Ground Cover	Classification and correlation	
Net Primary Productivity	Related to IPAR, improved with mixel data.	Peterson 1997; Peddle et al 1996
Actual Evapotranspiration	Regional transpiration flux = transpirational efficiency x (NDVI x PAR)	Running and Hunt 1993
Moisture Availability		
Soil Moisture	Spectral reflectance transformation	Crist and Cicone 1984
Surface Water	Spectral reflectance and classification	Waring et al 1995
Leaf Chemistry, Fire, and Vegetation Stress		
Leaf Chemistry	Total canopy nitrogen, chlorophyll and lignin are strongly correlated to LAI	Peterson 1997
Fire Potential	Departure from average greeness (NDVI)	Burgan et al 1996
Fire History	NDVI composite data	Kasischke and French 1995
Insect/Disease Stress to Foliage	Correlation with vegetation index differencing	Royle and Lathrop 1997

An assessment in Table 7.4 is a proposed remote sensing approach that could be used to differentiate patches on the basis of the elements illustrated in Table 7.3. This provides an indication of the complexity of the remote sensing enterprise if more than one or two biophysical attributes contributing to patch identification are to be captured. A range of low, medium and high spatial resolution imagery and a variety of image processing methods are required to enable complete acquisition of the various input variables that might be necessary in the biodiversity monitoring program. For example, patches defined as homogeneous cover types on the basis of conifer/deciduous/mixedwood could be readily monitored using a Landsat TM-type system and the methods outlined earlier (e.g., NDVI transformations, classification, mapping differences over time). Broad cover types might change very slowly and lag behind dramatic differences in NPP or photosynthesis that can occur within a cover type. If patches were defined on the basis of NPP; however, much greater understanding of the spatial distribution of the processes involved (higher spatial resolution) would be required in order to detect actual changes in patch dynamics associated with a landscape. Waring and Running (1998) point out, for example, that Oregon clearcuts attained maximum leaf area within a few years of harvesting when mapped using NOAA AVHRR data. Subsequent model estimates of NPP – which are highly sensitive to LAI estimates - approximated that occurring in adjacent, undisturbed old growth forests.

Table 7.4 Possible approaches to detect biophysical attributes pertinent to a biodiversity monitoring program

BIODIVERSITY ELEMENT		RECOMMENDED APPROACH			
		Sensor Package Image Resolution	**Image Processing Method**	**Field Requirements**	**Output Format**
Abiotic / Biotic	Broad Community Type	1	1	1	3
		1	1	1	3
Plant Species Composition	Canopy	2	1	2	3
	Understory	3	3	2	3
Vegetation Structure	Stand Density	3	4	3	2
	Stand Height	3	3	3	2
	Canopy Closure	3	2	3	3
	Canopy Gaps	3	2	3	3
	Seral stage	3	2	2	3
Photosynthesis and Related Processes	Absorbed Photosynthetically Active Radiation (APAR)	2	1	2	2
	Leaf Area Index	2	3	2	2
	Vegetative Biomass	2	1	2	2
	Net Primary Productivity	2	3	2	2
	Actual Evapotranspiration	2	1	2	2
Moisture Availability	Surface Water	2	1	1	3
	Soil Moisture	2	1,3	2	2
Leaf Chemistry, Fire, and Vegetation Stress	Leaf Chemistry	3	1	3	2
	Crown Transparency	3	3	2	2
	Fire History	2	1	2	1
	Insect Damage to Foliage	2	2	3	2
	Disease Damage to Foliage	2	2	3	2
		1 = Low	1 = Pixel	1 = Little	1 = GIS
		2 = Medium	2 = Texel	2 = Moderate	2 = Statistics
		3 = High	3 = Mixel	3 = High	3 = Image Map
			4 = Fexel		

In the CEOS Pilot Project proposed for the Global Observations of Forest Cover project (Ahern et al. 1998) a range of products from image classifications to continuous variable estimation will be generated. Of interest are: remotely sensed fine- and coarse-scale land cover; fire occurrence and burned area estimates; harvest, regeneration and afforestation classes; biomass; and direct observation of LAI, FPAR and PAR which are necessary to derive net primary productivity using process models at the landscape scale. NPP estimates, in turn, are an essential component of all carbon budget calculations (Running and Coughlan 1988; Franklin et al. 1997a,b). In attempting to address this global application, forest cover is based on actual cover rather than potential cover. Furthermore, mapping units must consider physiognomic characteristics, floristic elements are less important, and ancillary ecosystem information may be used to imply possible community composition.

Measures of patch diversity are clearly dependent on the definition of a patch, the consistency of the techniques used to identify and map patches using the specified elements, and the homogeneity of other attributes that might be included within the patch. In one multiple resolution mapping project in support of a New England GAP analysis, Slaymaker et al. (1996: p. 87) distinguish between *'fundamentally different categories, one based on reflectance of energy and the other based on human perceptions of what constitutes a community of plants'*. They used photointerpretation applied to airborne video data to guide the classification of Landsat TM imagery into nine or more mixed species of hardwood forest classes as input to a larger, vertebrate distribution mapping project. For monitoring biodiversity via remote sensing, we must first decide *what constitutes a biodiversity element at the ecosystem level* based on ecological theory (see next section). The biophysical nature of the biodiversity element will then determine whether patches of remotely sensed information can be directly analyzed or whether ancillary data will contribute to the patch definition and mapping.

Many phenomena are not naturally divided into discrete spatial units; instead, boundaries must be chosen from variables that gradually change across space (Foody 1996). For example, the boundaries between different vegetation types are blurred when one species smoothly intergrades into the next. For mapping forest stands, the line between a mixed conifer and pure conifer stand could be drawn in several places, as puzzling to determine from the ground as from the air. Increasing information does not necessarily ease the choice. A higher resolution image may actually expand the complexity of the problem by widening the variance of information. For digital images, algorithms have been devised to circumscribe patches automatically based on pixel values or their derivations. Patch boundaries for selected conditions can be determined from digital maps or remote sensing images using several techniques (Urban 1998):

1) Adjacent pixels with like values, such as reflectance, can be clustered together.
2) By detecting defined properties of edges, patches can be outlined. For example, the boundaries of patches can be circumscribed from continuous variables by detecting locations with significant rates of change in the variable (Fortin 1994).
3) Starting from a single patch, between region variance can be maximized to partition statistically homogeneous patches, so that the variance within an element is less than that among elements (Pielou 1984).
4) Patches can be clustered hierarchically, with a constraint on adjacency. Groups will only be joined if spatially contiguous (Legendre and Fortin 1989).
5) Multiple values for each pixel (spectral and DEM derivatives) can be clustered with classification algorithms based on multivariate similarities.

Patch size, shape and spatial arrangement in the landscape can be readily calculated from digital maps or land cover classes interpreted from imagery. When considering the temporal framework for biodiversity monitoring, it seems increasingly obvious that only a digital methodology will have the inherent rigour that will be required to ensure confidence in mapped features, such as patches, however defined. In essence, if digital maps are required to monitor patch size, shape, composition, and spatial arrangement, then the digital maps should be produced using digital remote sensing methods. For example, Lowell and Edwards (1996) have commented that *"recent estimates of map accuracy from photointerpretation of forested areas indicated that disagreement is as high as 40% to 50%… The result is that forest stand polygons cannot be compared directly from one date to the next"*. There appears to be major problems with a non-digital remote sensing approach to patch mapping and that only remote sensing from satellites (with aerial imagery to support the program) has the potential to form the foundation for the next generation of land cover maps (Gaydos 1996). In summary, in digital mapping, digital remote sensing provides greater spectral resolution, comparable spatial detail, large area coverage, repeatable observation, digital format, lower cost, and higher accuracy.

Relationship Between Ecological Hypotheses and Measures of Biodiversity

For inventorying, monitoring, and modeling biodiversity, researchers have used remote sensing to detect ground patterns (patches) that are correlated with habitat diversity and species richness. Ecological hypotheses concerning the geographic distribution of habitat and species richness (Wickham et al. 1997) influence how patches are defined and thus the types of biodiversity elements measured. For example, the *heterogeneity* hypothesis states that spatial heterogeneity is positively correlated with species richness of an area (Wickham et al. 1997). Under this principle, biodiversity can be measured as almost any type of patch diversity within a landscape. Patch diversity can be assessed at various scales using vegetation composition and structure (Jorgensen and Nohr 1996), geomorphology (Burnett et al. 1998; Nicols et al. 1998), ecoclimatic stability (Fjeldsa et al. 1997), levels of photosynthetic activity (Walker et al. 1992), and so on.

The *available energy/productivity* hypothesis states that the productivity of large-scale environments is positively correlated with species richness (Wickham et al. 1997). Areas of high net primary productivity (NPP) have more resources to partition among competing species and can thus support a greater number of species and larger populations than areas with low net productivity (Walker et al. 1992). However, the relationship between species richness and productivity is not completely straightforward, depending on the level of productivity, the particular species and the balance between available soil nutrients and light (Rosenzweig and Abramsky 1993; Tilman and Pacala 1993). Using remotely sensed data, NPP is a quantifiable biodiversity element and can be modeled from estimates of photosynthesis, woody biomass, cover type, and evapotranspiration rates (Franklin et al. 1997a, 1997b; Gholz et al. 1997; Running and Hunt 1993). Following assumptions of the energy/productivity hypothesis, comparisons have been made between ground-based measures of species richness and vegetation indices based on satellite data. For example, the relationship between avian species diversity and annual vegetative biomass was evaluated in Senegal using the Integrated Normalized Difference Vegetation Index (INDVI) obtained from NOAA AVHRR satellite data (Jorgensen and Nohr 1996). In California, moderately strong correlations between plant species richness and NDVI values (NOAA AVHRR data) were found, but varied depending on date and the species life form (Walker et al. 1992).

The *species-habitat* or *niche* hypothesis is based on the concept that every species has a set of environmental requirements for life and reproduction (Wickham et al. 1997). Species richness in a community or landscape is a function of the number of niches. From this viewpoint, several studies have combined GIS and remotely sensed data to predict patterns of species distributions based on habitat requirements (Aspinall and Veitch 1993; Avery and Haines-Young 1990; Lauver and Whistler 1993; Stoms 1992). Others have combined environmental factors in a GIS to produce ecological land classifications useful for habitat delineation and biodiversity assessment (Davis and Dozier 1990; Stoms 1992; Stoms and Estes 1993). Also following the species-habitat concept, the presence of an indicator species has been used to predict the presence of other species associated with its habitat (Debinski and Brussard 1992).

Using a combination of ecological theories, Bass et al. (1998) suggest that emitted thermal energy can be used as an indicator of forest biodiversity. According to succession theory, mature ecosystems contain specialized, energy efficient species that fit into narrow, ecological niches. Specialized species replace more generalized, less energy efficient species with time. According to the available energy/productivity hypothesis, a greater number of energy efficient species can occupy an environment than can more generalized, energy inefficient species. Consequently, ecosystems develop towards more efficient utilization of high-level energy and greater species diversity. Bass et al. (1998), referring to statements of Kay and Schneider (1992) and Schneider and Kay (1994) on thermodynamic theory, suggest that less thermal energy will be released from systems that more efficiently utilize and degrade incoming energy. Thus, more mature forest ecosystems with higher levels of species diversity will emit less thermal energy than immature forest ecosystems. Areas of low thermal emittance, identified as relatively cold spots in remotely sensed infrared imagery, correlated with less mature forest ecosystems (Bass et al. 1998). Further research is required to understand whether these relationships hold for other succession systems besides the particular Douglas fir forest investigated (Bass et al. 1998) and whether they hold when conditions vary that affect thermal emittance, i.e., time of year, time of day, cover albedo, cover type and so on.

Influential to the language of landscape ecology, the theory of *island biogeography* asserts that species richness is a function of island area and colonization rate (MacArthur and Wilson 1967). At equilibrium, the local extinction rate is inversely related to area; that is, higher rates of extinction occur in smaller areas. Rates of immigration to islands decline with distance from the mainland colony. Therefore, larger islands closer to the mainland will have greater species richness than smaller more distant ones. Similar relationships between species richness and patch size, distance between patches and colonizing populations have been attributed to terrestrial systems. Forest landscapes have been described as being oceans with islands (patches) of habitat; as forests become fragmented by disturbance, patches become smaller and more distance from one another (Harris 1984). However, this model has less application in terrestrial systems in which patch area has a limited relationship to number of species.

Following island biogeography theory, metapopulation theory has contributed conceptually to landscape ecology (Urban 1998). A metapopulation is a group of discrete localized subpopulations with dispersal among them. Most population dynamics occur within the subpopulation; however, dispersal between populations on a regular basis promotes gene flow and helps to decrease the probability of population extinction and fluctuations in population size. In order for a metapopulation to function, habitat patches must be accessible; otherwise, isolation of subpopulations will occur. The composition, structure, and quality of corridors affect the connectivity; that is, the degree to which organisms can move between subpopulations through the landscape matrix, and influence the size of the metapopulation (Anderson and Danielson 1997). To maintain subpopulation balance, the number of migrating individuals should not exceed that of those emigrating. Potential breeding habitat must exist and reproduction must successfully replace losses due to mortality; otherwise, local extinction will occur. The size and shapes of habitat patches are important because area-related edge effects may influence reproduction.

Several predictions concerning the pattern of patches within a landscape and species richness follow from island biogeography theory, metapopulation theory, patch dynamic theory and others (Forman 1987; McGarigal and McComb 1995; Urban 1998). First, higher species richness will be found in landscapes of diverse patches (echoing the habitat diversity theory). Second, landscapes having corridors that act as conduits and connected patches that act as stepping stones for moving objects are likely to have greater species diversity. Third, in landscapes with factors affecting productivity and reproduction positively, greater species richness will occur. Finally, species richness will be influenced by the edge/area ratios of patches within the landscape. The direction of the effect will depend on species habitat requirements; for example, whether the species is edge or core dwelling. Following from these predictions, a biodiversity monitoring program should measure and track features such as the patch size and diversity, the distance and connectivity between like patches, and the edge/area ratios of patches within the landscape (Noss 1990). Further discussion of these issues is found in the next section.

Quantifying Landscape Pattern After Patch Delineation

Landscape pattern can be quantified from measures of the composition and structure of landscape patches (Table 7.5) mapped from elements obtained by remote sensing. From measures of cover type, LAI or other defined elements, patch relationships that affect landscape dynamics, i.e., diversity, complexity, association and connectivity, can be calculated. The variety and relative abundance of patch types are measures of composition and include patch richness, patch diversity, and diversity indices. The size distribution of patches, the dispersion of patch types throughout the landscape, the contrast among patches, the patch shape complexity, the contagion or clumping of patch types, and the corridors between patches are structural components of the landscape that can be quantified (McGarigal and Marks 1995; Urban 1998).

Quantification of spatial relationships and patterns allows comparisons between different areas, giving clarification to land management decisions that affect biodiversity. By monitoring patch relationships over time, important changes influencing ecological phenomena, such as animal movements, hydrology, spread of disturbance, and net primary productivity can be detected (Turner and Ruscher 1988; Turner 1990). In addition, by quantifying spatial relationships and patterns, variables are provided for models to test underlying processes predicted by ecological theories. Issues concerning broad spatial scales and the ecological effects of the spatial patterning of ecosystems belong within the discipline of landscape ecology (Turner 1989).

Table 7.5 Description of measures of landscape pattern
Based on Metzger and Muller 1996, O'Neill et al. 1988; Urban 1998

Landscape Measure	General Description
Composition	The variety and relative abundance of patch types
Richness	The number of different patch types
Diversity	The relative abundance of different patch types
Structure	The configuration of the landscape
Size distribution	The relative abundance or frequency of patches in different size classes
Dispersion	The distribution of patches with respect to each other, regularly dispersed vs. clumped
Contrast	The relative difference among patch types
Shape complexity	The relative amount of edge per unit area; the fractal dimension
Adjacency/contagion	The tendency of a patch type to occur next to another patch type
Connectedness	The functional joinings between patches
Boundary	The transition zone between patches
Boundary Richness	The number of different boundary types
Boundary Convergence	The proportion of of points where more than three patches converge
Boundary Diversity Index	The number and the area evenness of boundary types

The transition zones between patches, the patch boundaries, perform important ecological functions, allowing passage of biotic and inorganic factors between patches and contacts between core and edge dwelling species (Metzger and Muller 1996). Boundaries resulting from anthropogenic activities (roads, fields, clearcuts) are generally sharper and less complex than those generated by natural processes, i.e., transitions between meadow and forest, or conifer and mixed conifer. When the reflectance values of a patch distinctly contrasts with those of adjacent patches (as is often the case with anthropogenic-based patches), accurate automatic identification from remotely sensed images is possible. Points where the boundaries of three or more landscape elements congregate may be important centers of resources and corridors for wildlife (Forman and Gordon 1986). For these reasons, the zones between patches and their intersections are important features to describe and quantify in a landscape level biodiversity assessment. Metzger and Muller (1996) offer methods and indices for characterizing boundaries. Boundaries are defined as *"the set of pixels of one landcover type in contact, orthogonally or diagonally, with at least one pixel of another class"* (Metzger and Muller 1996: p. 66). Each boundary is then classified according to the landcover classes in contact, including convergency points where two or more classes merged. The proportion of convergency points, the number of boundary types and the diversity of boundary types are used as variables for indices of landcover and boundary proportion.

A confusing and overwhelming number of metrics has been developed to quantify landscape composition and structure (Table 7.6). Modeled on ecological theory, these metrics attempt to quantify aspects of landscape pattern thought to reflect or influence underlying ecological processes, i.e., patch area, shape, edge, core area, nearest neighbor, diversity, richness, evenness, contagion, interspersion, juxtaposition, configuration, connectivity and circuity (Table 7.6). Certain metrics require information concerning habitat requirements for the species of interest. For example, core area calls for the habitat area requirements of targeted species as input. However, most other measures, such as the mean shape average and landscape diversity indices, are independent of underlying ecological process or habitat requirements, relying strictly on the geometric and spatial relationships of patches. For diversity and landscape metric formulas, see those compiled in several lists (Magurran 1988; McGarigal and Marks 1995; Metzger and Muller 1996; O'Neill et al. 1988; Riitters et al. 1995). Given the many metric options, deciding on a set suitable for a particular study has been problematic. The metrics chosen should offer unique information and have ecological relevance. In addition, certain metrics may be sensitive to map scale, number of classes, size and shape of patches, spatial distribution of patches and other factors. Using sensitive metrics for landscape comparisons could result in misinterpretation, if conditions are not held constant. Recent studies have been conducted to evaluate correlations and the effects of various variables on landscape measures, in order to understand their properties and aid in the selection of an appropriate set.

Table 7.6 A selection of landscape indices
Based on Frohn (1998); Haines-Young and Chopping (1996); Mead et al (1981); McGarigal and Marks (1994) and O'Neill et al (1988)

	Index Type	**Index Description/Definition**
Area Metrics	Total Landscape Area	
	Largest Patch Index (%)	Percentage of area accounted for by the largest patch
	Number of Patches	
	Patch Density	Number of patches per unit area
	Number of Classes	
	Mean Patch Size	
	Patch Size Standard Deviation	Absolute measure of patch size variability
	Standard Deviation of Mean Patch Size	Percentage variation (relative)
	Dominance	The degree to which proportions of each patch type on the landscape predominates
	Permeability	Area of unsuitable patches (for transmission) divided by the total area
Edge Metrics	Total edge	Total length of all patch edges
	Edge density	Length of patch edge per area
	Contrast-weighted edge	Length of patch edge per area, weighted by edge contrast
	Total edge contrast index	The degree of contrast between a patch and its immediate neighborhood
	Mean edge contrast index	The average contrast for patches of a particular class
	Area-weighted MECI	Patches are weighted by their size
	Isolation	% edge adjoining similar patch types
Shape Metrics	Landscape shape index	Measures of landscape compared to a standard
	Mean shape index	Average patch shape (perimeter/area) for a patch class
	Area-weighted mean shape index	Patches are weighted by their size, then mean shape calculated for class and landscape
	2 x log fractal dimension	Departure of landscape mosaic from Euclidean geometry
	Fractal Dimension	The complexity of patch shape on a landscape
	Mass fractal dimension	The total complexity of the map matrix
	Mean patch fractal dimension	Based on the fractal dimension of each patch
	Area-weighted mean patch fractal dimension	Patches are weighted by their size, then fractal dimension calculated for class and landscape
	Elongation	Diagonal of smallest enclosing box divided by the average main skeleton width
	Square Pixel (SqP)	The shape complexity of patches on a landscape
Core Area Metrics	Core area	Area of interior habitat defined by specified edge buffer width
	Number of core areas	
	Core area density	Number of core areas per unit area

	Mean core per patch	
	Core area standard deviation	Absolute measure of core area variability
	Disjunct core	Within a patch, 2 or more disjunct core areas
	Total core area index	The percentage of a patch comprised of the core area
Nearest Neighbor Metrics	Nearest-neighbor distance	The distance of a patch to the nearest neighboring patch of the same type based on edge to edge distance
	Proximity index	The size and proximity distance of all patches whose edges are within a specified radius of the focal patch
	Mean nearest-neighbor distance	For a class or for the landscape as a whole
	Nearest-neighbor distance standard deviation	A measure of patch dispersion
	Spatial autocorrelation	Patch type spatial correlation; patch type distribution
	Mean proximity index	For a class or for the landscape as a whole
	Interpatch Distance	
Diversity, Richness and Evenness Metrics	Shannon's diversity index	A single number that captures both abundance and variety. The amount of information per patch
	Simpson's diversity index	A single number that captures both abundance and variety. The probability that any types selected at random would be different types.
	Patch richness	Number of different patch types
	Patch richness density	Patch richness standardized to per area
	Relative richness density	Richness as a percentage of the maximum potential richness
	Shannon's evenness	Relative abundance of different patch types
	Simpson's evenness	Relative abundance of different patch types
Interspersion / Juxtaposition, Contagion and Configuration Metrics	Contagion	The tendency of landcovers to clump within a landscape
	Dispersion	Degree of fragmentation/complexity of patch boundaries
	Association	Concentration of spatially distributed attribute variables
	Interspersion	The number of pixels in a 3x3 square that are of a different habitat than the central pixel
	Juxtaposition	Habitat edges are weighted for quality for each organism and those surrounding the central pixel in a moving window are summed.
	Fragmentation	The tendency of landcovers to break into small pieces within a landscape
	Patch Per Unit area (PPU)	The degree of fragmentation of patches on a landscape
Connectivity and Circuitry	Connectivity	Number of links in a network divided by the maximum number of links

	Circuitry	Number of circuits in a network divided by the maximum number of circuits

Correlation among metrics. Because many landscape metrics share fundamental measures of patch size, shape, perimeter-area ratio and inter-patch distance, many are related to one another (Cain et al. 1997; Hargis et al. 1998; Li et al. 1993; Riitters et al. 1995). To find a set of uncorrelated landscape metrics, Riitters et al. (1995) performed a multivariate factor analysis on 26 metrics calculated for 85 land use and land cover maps. Factor analysis seeks to uncover the underlying pattern and structure within a set of multivariate observations by identifying common dimensions among the variables. Eighty-seven percent of the metric variation was explained by the first six factors (Table 7.7), which were interpreted as composites of correlated measures representing average patch compaction, overall image texture, average patch shape, patch perimeter-area scaling, number of attribute classes, and large-patch density-area scaling. The sixth factor represented only one map and for that reason was treated as an outlier. Of the metrics tested, five key indices were identified as best representing the first five factors. The five indices chosen based on having the highest loading on the factor were average patch per perimeter-area ratio, Shannon contagion, average patch area normalized to the area of a square with the same perimeter, patch perimeter-area scaling, and the number of attribute classes (Table 7.7).

Table 7.7 Correlated groups of metrics

Factor	**Group of metrics**	**Metric best representing group**	**Factor**	**Group of metrics**
	Riitters et al. 1995	**Riitters et al. 1995**		**Cain et al. 1995**
1	Average patch compaction	Average patch perimeter ratio	1	Texture
2	Image texture	Shannon contagion	2	Patch shape and Compaction
3	Average patch shape	Average patch area normalized to the area of a square with the same perimeter	3	Patch shape and Compaction
4	Patch perimeter-area scaling (fractal measures)	Patch perimeter-area scaling	4	Perimeter-area scaling
5	Number of attribute classes	Number of attribute classes	5	Perimeter-area scaling
6	Large-patch density-area scaling	Not considered relavant	6	Number of attribute classes

In another (multivariate) study, the statistical independence of 28 metrics was tested on maps derived from Landsat imagery (Cain et al. 1997). Map variables that were evaluated include spatial resolution, number of attributes, method of delineating patch boundaries, analysis units (watershed vs. rectangle) and map type (raster vs. vector). A multivariate factor analysis of the metrics was conducted on each map, followed by a comparison among the different types of maps. Overall, the types of metrics comprising the first six factors (92% to 97% of variation) were similar to those listed above (Riitters et al. 1995) (Table 7.7). In terms of statistical properties, the most important component for all data sets was texture (as measured by the Maximum Attribute Class Proportion or Shannon Contagion), being stable to spatial resolution, number of attributes and patch boundary methods (Cain et al. 1997). Depending on the type of map, however, patch shape and compaction metrics were either loaded together on one factor or individually on the second and third factors, while perimeter-area scaling metrics either loaded on the fourth or fifth factor (Cain et al. 1997) (Table 7.7). Patch shape and compaction metrics may belong to the same dimension that *"is being measured in slightly different ways"* (Cain et al. 1997). Because different combinations of measures loaded together for different types of maps, Cain et al. (1997) propose that patch shape and compaction measures may be sensitive to changing map scales. Measures of interpatch distance, not analyzed by Riitters et al. (1995), were found to be independent of other measures in two separate multivariate analyses (Cain et al. 1997; Hargis et al. 1998).

The above studies (Cain et al. 1997; Hargis et al. 1998; Riitters et al. 1995) imply that in order to avoid erroneous interpretations and redundancy, comparisons of landscape structures should be made at the same scale (image resolution) using a set of statistically independent metrics. *"A meaningful interpretation of landscape metrics is possible only when the limitations of each measure are fully understood, the range of attainable values is known, and the user is aware of potential shifts in the range of values when applied to landscapes with different structural characteristics*." (Hargis et al. 1998: p.167). A related concern is the use of existing vegetation inventories, perhaps generated in an ad hoc manner (e.g., historical distribution vs. actual cover type) and, if based on aerial photointerpretation over time, without an understandable or credible error analysis for boundaries and polygon (or patch) labelling. The difficulties that might arise in using such data as input to a landscape metric analysis are described more fully later in this chapter within the context of an overall emphasis on completely digital methods of acquisition and analysis.

A summary table showing the influence of certain issues on specific metrics is provided in Table 7.8 and described briefly below. The review of issues affecting landscape metrics is not exhaustive, but serves as a caution against possible measurement errors that can result if used haphazardly. Patch diversity can be quantified, but depends on the definition of a patch and the selection of metrics to capture the essential features of the patch pattern.

Table 7.8 Summary of issues affecting landscape metrics from selected studies
Reference: 1 = Cain et al. 1997; 2 = Frohn 1998; 3 = Hargis et al. 1998; 4 = Benson and MacKenzie 1995.

	ISSUES						
METRIC	**Scale of Landscape**	**Number of Patch Classes**	**Patch Size**	**Patch Shape**	**Pixel Size**	**Raster Orientation**	**Spatial Distribution of Patches**
Contagion	little effect, 1	effect observed, 2	effect observed, 3	effect observed, 3	effect observed, 2	effect observed, 2	little effect, 3
Landscape Diversity	little effect, 1						
Fractal Dimension - Perimeter-Area	little effect, 1; some effect, 4		effect observed; 2, 3	effect observed; 2, 3	effect observed, 2		little effect, 3
Fractal Dimension - Mass			little effect 3	effect observed, 3			
Edge density			effect observed, 3	effect observed, 3			little effect, 3
Mean			effect				little effect, 3

Nearest Neighbor Distance			observed, 3				
Mean Proximity Index			effect observed, 3				little effect, 3
Average Patch Shape	some effect, 1						
Compaction	some effect, 1						
Average Patch Area	effect observed, 4						
Average Patch Perimeter	effect observed, 4						
Class %	effect observed, 4						
Patch Number	effect observed, 4						
Homogeneity	little effect, 4						
Entropy	little effect, 4						
Contrast	effect observed, 4						
Patch Per Unit Area		no effect, 2			no effect, 2	no effect, 2	
Square-Pixel			no effect, 2	no effect, 2	no effect, 2		

Image resolution. Benson and MacKenzie (1995) compared landscape parameters calculated from water and land classes using SPOT HRV, Landsat TM and NOAA AVHRR images of northern Wisconsin (low to medium image resolution) and simulated images with resolutions between those of HRV and AVHRR. Six simulated images were obtained by successively aggregating pixels to increase pixel size from 20 m to 1,280 m. For each image classified, different patch areas, shapes, and locations resulted. For example, small bodies of water that were detected at medium resolutions were not recorded at low resolution. Estimations of homogeneity and entropy were relatively invariant across the images. The percent water and number of lakes decreased as the grain size increased, while the contrast, the number of patches, the average lake area, perimeter, and fractal dimension increased (Table 7.8).

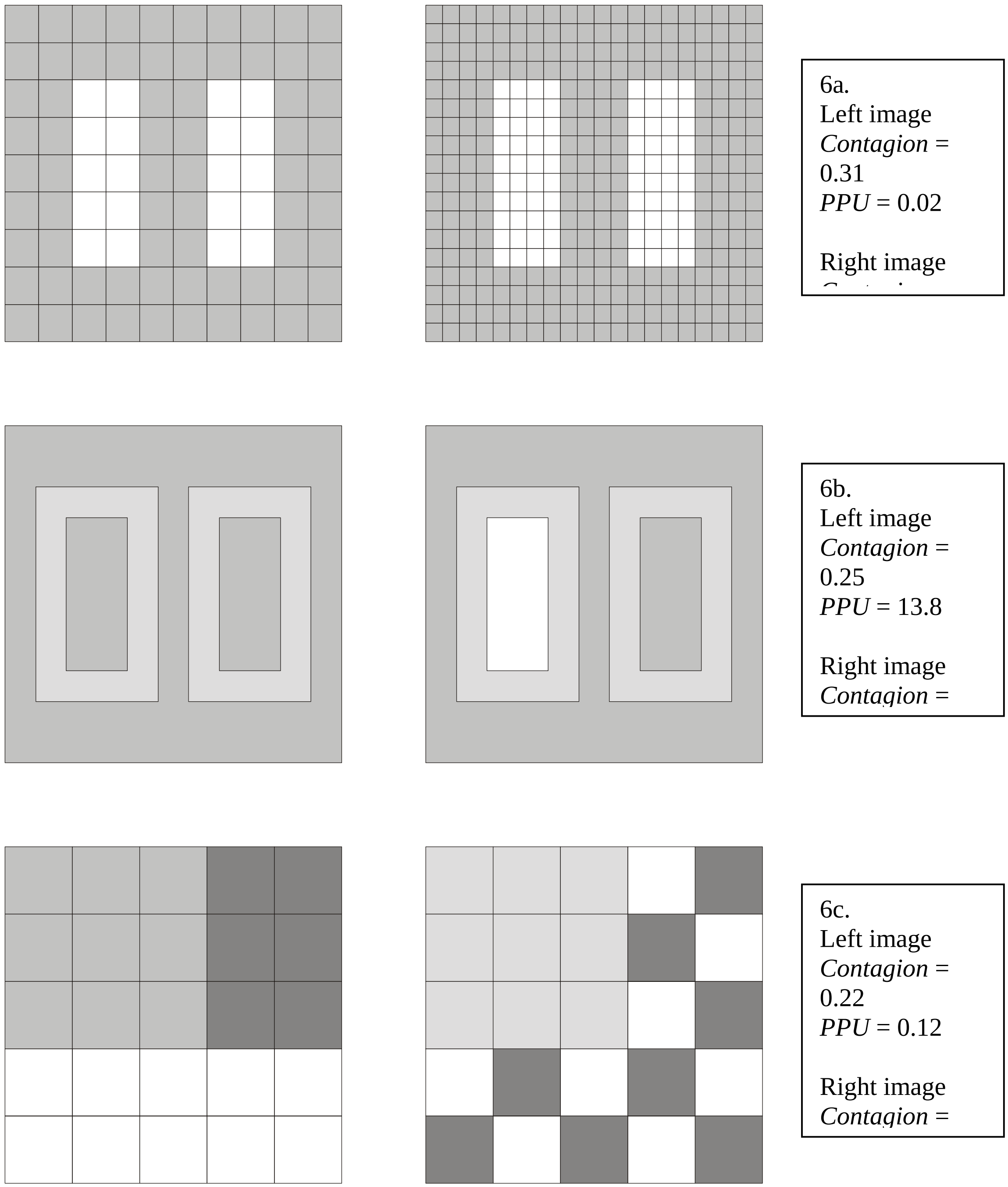
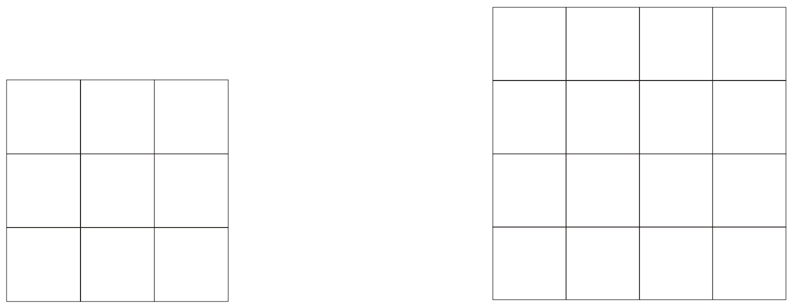


Figure 7.6. Frohn's Examples of Contagion and Fractal Dimension Calculations

a. The effects of pixel size changes on *Contagion* and *PPU* for identical ground patterns.

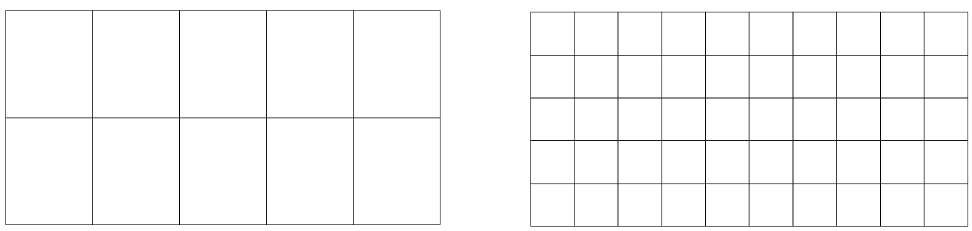
b. The effects of varying the number of landcovers on *Contagion* and *PPU*. *Contagion* increases with the increase in number of landcovers, while *PPU* remains the same.

c. A case where *Contagion* does not measure contagion. The figure on the left is a 5x5 image of three classes that appear contagiously distributed. The figure on the right appears fragmented with 17 patches for the three classes. However, the *Contagion* metric is lower than the fragmented image.



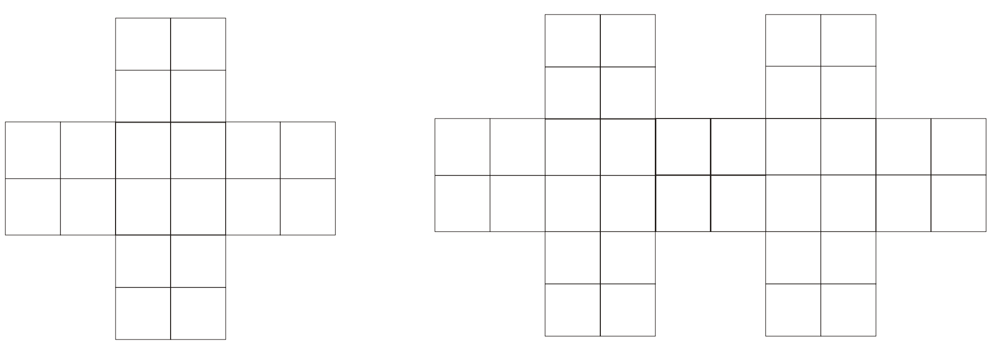
d.
Left image
Perimeter = 12
Area = 9
D = 2.26
D_p = 1.00
SqP = 0.00

Right image
Perimeter = 16
Area = 16
D = 2.00
D_p = 1.00
SqP = 0.00



e.
Left image
Perimeter = 14
Area = 10
D = 2.29
D_p = 1.09
SqP = 0.10

Right image
Perimeter = 28
Area = 40
D = 1.81
D_p = 1.06
SqP = 0.10



f.
Left image
Perimeter = 24
Area = 20
D = 2.20
D_p = 1.20
SqP = 0.37

Right image
Perimeter = 40
Area = 36
D = 2.06
D_p = 1.29
SqP = 0.60

Figure 7.6 Continued
d. The perimeter, area, *Fractal Dimension* (D), modified *Fractal Dimension* (D_p), and *SqQ* values for two different sized squares. Notice that *Fractal Dimension* gives invalid results while the modified *Fractal Dimension* and *SqQ* give valid results.
e. The perimeter, area, *Fractal Dimension* (D), modified *Fractal Dimension* (D_p), and *SqP* values for the same rectangles that differ only in pixel size. Perimeter and area based on pixel units. Dp decreases slightly as pixel size decreases. D gives an invalid result with a large decrease with decreasing pixel size. SqP gives the same value for both rectangles.
f. The perimeter, area, *Fractal Dimension* (D), modified *Fractal Dimension* (D_p, and *SqP* for two different shapes. Notice that *Fractal Dimension* gives invalid results and indicates that the shape on the

left is more complex than the shape on the right. The modified *Fractal Dimension* gives valid results and indicates that the shape on the right is slightly more complex than the shape on the right. SqP also gives valid results and indicates that the shape on the right as clearly more complex than the shape on the left.

Pixel size. The pixel size of a digital image may affect certain landscape measures (Table 7.8). For instance, the number of pixels that are adjacent to one another governs the metric contagion, a measure of patch aggregation. Although patch aggregation does not change with smaller pixel size, the value of contagion increases due to the increased number of pixels that are adjacent to one another (Frohn 1998) (Figure 7.6a). Frohn (1998) introduced a novel metric, Patch Per Unit Area (PPU), as an alternative measure of patch aggregation. PPU is insensitive to pixel size since only the total number of pixels; the total number of patches and a scaling constant are used to calculate its value. Pixel size also alters fractal dimension (D), a measure of patch complexity that is estimated using a linear regression of patch area and patch perimeter in pixel units (rather than metric units). Frohn (1998) developed the modified fractal dimension (D_p) that is less sensitive to pixel size (Figure 7.6e), as well as to other issues affecting landscape metrics (Figure 7.6d-f). However, an even more improved patch complexity metric is Frohn's (1998) Square-Pixel (SqP), depending only on the total area and total perimeter of all pixels in the study area and having complete insensitivity to the number of pixels within a patch (Figure 7.6e).

Number of patch classes. In addition to measuring patch clumping, contagion takes into account the proportional representation of patch types in the landscape. Consequently, the number of patch classes can influence contagion, even though no change in spatial pattern has occurred. For example, in an analysis of metric stability under varying image parameters, contagion increased from 0.25 to 0.41 as the number of classes increased from two to three (Frohn 1998) (Figure 2.6b). Not dependent on the proportion of patch classes, PPU remained unaffected in the same example (Frohn 1998) (Figure 7.6b).

Patch size. Nine landscapes with patterns of increasing fragmentation were simulated while controlling the size and shape of patches and the type of growth (enlarging patches, abutting patches and buffered patches) (Hargis et al. 1998). Patch size showed significant effects on measures of edge density, contagion, mean nearest neighbor distance (for thinly distributed patches), the proximity index, and perimeter-area fractal dimension (for abutting patches) (Hargis et al. 1998). Frohn (1998) noted that different sized squares result in various measures of fractal dimension (D) (Figure 7.6d), caused by diverging rates of change for area (exponential) and perimeter (linear) with increasing size. By including a constant of proportionality for the modified fractal dimension D_p, that expresses the relationship between perimeter and area, this problem is eliminated (Figure 7.6d) (Frohn 1998). For this example, SqP remains constant at 0, denoting no perimeter deviation from a perfect square (Figure 7.6d).

Patch shape. The effect of shape on landscape metrics was investigated using rectangular and small-irregular patches in artificial landscapes (Hargis et al. 1998). Edge density, contagion, perimeter-area fractal dimension and mass fractal dimension (for enlarging patches with increased disturbance) were significantly affected by patch shape (Hargis et al. 1998). In Frohn's study (1998), the complexity of the patch shape is not always recorded by fractal dimension (D), as indicated by the lower D value for the obviously more complex image (Figure 7.6f). Note that the value of SqP increases as patch complexity increases (Figures 7.6d-f).

Raster orientation. Raster orientation changes the proportions of pixel adjacency (Frohn 1998). By shifting an image 45 degrees, the straight edges of a rectilinear patch become serrated as the corners of edge pixels jut into the adjacent patch; this shift effectively increases the proportion of adjacent pixels. Because contagion is determined by calculating pixel adjacencies, raster orientation affects values of contagion, but not PPU (Frohn 1998).

Spatial distribution of patches. Contagion, mean nearest neighbor distance, mean proximity index, and mass fractal dimension are relatively insensitive to the spatial arrangement of patches (Hargis et al. 1998). In addition, edge density and perimeter-area fractal dimension are nearly unaffected by the spatial composition of patches (Hargis et al. 1998). Hargis et al. (1998) state that they know of no landscape metric that quantifies the spatial distribution of patches. The spatial distribution of patches has an important impact on certain ecological processes that depend on connectivity including the flow of organisms, pollen and seeds across the landscape. Finding measures to quantify the spatial distribution of patches is important for detecting changes that affect these basic biological processes of distribution and migration.

Understanding how image resolution, pixel size, number of patch classes, patch size, patch shape, and raster orientation affect measures of landscape pattern is especially critical when analyzing the types and quantities of change in the landscape over time. For change detection, whenever possible, images should be compared that share the same image resolution, pixel size, and raster orientation. When comparing images using metrics affected by variables that cannot be held constant, i.e., patch size and shape, other unaffected metrics should be included in the study as controls.

Interpreting the ecological relevance of landscape composition and structure has been problematic as well, remaining a fertile area for further research. However, even without a complete understanding of how landscape patterns affect the complex biotic/abiotic dynamics within and among ecosystems, measures of landscape composition and pattern are important measures of biodiversity in their own right, as direct measures of biodiversity at the regional landscape level of organization.

Landscape Disturbance

For monitoring biodiversity of large areas, as at the provincial scale, important changes to the mosaic of land covers that influence habitat and ecological processes must be detected and described. Although the condition of Alberta’s landscape before European settlement is not entirely understood, today’s patterns can act as baseline from which to make future comparisons. Natural and human disturbances, ecological succession, and recovery from previous disturbances are all forces that modify ecosystem pattern within the landscape. These forces alter ecosystem heterogeneity with various effects on species diversity. A small disturbance may increase the heterogeneity of a landscape and increase habitat niches. For example, a fire or windthrow opens the forest floor to sunlight, promoting growth of herbaceous plants, grasses, and bushes, improving habitat quality for a variety of organisms, such as pollinating insects, ungulates and bears. A severe disturbance, such as a major landslide or flood, either may decrease landscape heterogeneity by removing the elemental configuration or increase heterogeneity by changing only a part of the structure (Forman and Gordon 1986).

In addition to horizontal patterns, disturbance affects the vertical heterogeneity of ecosystems and landscapes. In an undisturbed landscape, horizontal landscape structure tends to become increasingly homogeneous with time (with maturity), while vertical structure becomes higher and more heterogeneous (Forman and Gordon 1986). With disturbance, landscape structure tends toward the inverse pattern; heterogeneous horizontal structure and more homogeneous vertical structure (Turner and Bratton 1987). However, in some cases both vertical and horizontal diversity are affected similarly. For example, a catastrophic fire or large clearcut reduces the structural heterogeneity of a forest by eliminating both the vertical layers and horizontal patches of vegetation.

Forest habitat diversity has been linked to vertical structural complexity; that is, to canopy density, variation in tree size, coarse woody debris, understory density, litter depth, presence of snags and fallen trees (Carey and Johnson 1995; Hansen et al. 1993, 1995; Imhoff et al. 1997; Rickers et al. 1995). Vertical structure is an important element to track in a landscape level forest biodiversity monitoring program because of its relationship to underlying ecosystem level biodiversity. Vegetation structural types that contribute to bird habitat quality have been discriminated using remotely sensed SAR backscatter data (Imhoff et al. 1997). Vertical complexity has also been captured by large footprint lidar that detects the top of the canopy, individual crowns at various heights and the ground in the same waveform (Lefsky et al. 1999).

Forman (1995) describes five disturbance processes that change a landscape, influence habitat loss, and that can occur simultaneously. The types of alterations to the landscape pattern produced by these processes are distinctive, providing target patterns to detect in a monitoring program. Perforation results in the creation of holes in the patch or landscape. Dissection cuts a landscape area by equally wide linear features, such as roads and pipelines. Fragmentation breaks and separates a patch into segments. Shrinkage causes the sizes of patches to decrease. Attrition results in a patch's disappearance.

Fragmentation of a landscape occurs when land cover patches are dissected by disturbance. Fragmentation leads to smaller patches, more distant patches, and increases in edge/area ratios. Organisms sensitive to patch size may be sensitive to habitat fragmentation and shrinkage. For example, the varied thrush (*Ixoreus naevius*) is a forest interior species that avoids forest edges (Hansen et al. 1991). If a large percentage of this bird's forest habitat were fragmented, its ability to survive would markedly diminish.

Landscape fragmentation and other disturbance processes can affect the distance and corridors between patches in the matrix. Movement of species between habitat patches occurs when the distance between patches is not too great and when corridors connect the patches. Dissection and fragmentation usually decrease the connectivity over an area in uninterrupted corridors or matrix (Forman 1995). Isolation of habitat patches is likely to result in a decrease or extinction of existing populations, especially for those species with large ranges and little tolerance for crossing less than optimal habitat. For one such species, the elk (*Cervus elaphus*); for example, extensive sections of adjoining habitat are required (Silbaugh and Betters 1997).

For evaluating patterns of landscape disturbance, measures that quantify patch size, interpatch distance, spatial association of patches, edge to area ratios, corridors and connectivity, etc. are particularly helpful (Table 7.6). In addition, fragmentation has been associated with the spatial density of roads, pipelines, and other dissection factors that divide patches and sever corridors (Tinker et al. 1998). For example, the extent of clearcuts and the distribution of roads in twelve watersheds in the Bighorn National Forest of Wyoming were determined from a time series of four maps and compared to the fragmentation of these maps as revealed by 30 landscape pattern metrics (Tinker et al. 1998). The extent of fragmentation was shown to increase in relation to the existence of roads and clearcuts.

By frequently monitoring landscape composition and pattern, signs of landscape disturbance would warn of approaching changes with sufficient time to respond against irreversible damage. Tolerance thresholds for these signs would include, for example, developing lower limits for patch size decreases and upper limits for the density linear features.

Remote Sensing Products for Biodiversity Monitoring

Numerous local and regional groups have been working with the Canadian Council of Forest Ministers (1997) criteria and indicators of sustainable forest management with a view to devising and implementing local indicators for biodiversity monitoring (e.g., Etheridge and Daigle 1998; Dempster 1998). Some of these efforts have made reference to remote sensing approaches (bottom-up) while others proceed without reference to data source (top-down). Although a few appear to have focussed on plant communities, others have considered disturbance classes and habitat in a continuum. All face the practical issue at one time or another: *How to monitor the agreed-upon indicators?* The first place to begin answering this question is to match, if possible, a set of classes, which might be a starting point for a remote sensing classification leading to the desired monitoring element. In the literature this has been presented in the form of classification systems aimed at fragmentation analysis, habitat mapping or biodiversity monitoring. A more general approach is to decide if the classification will be general purpose or specifically designed. For example, it is doubtful whether there would be complete overlap between classes mapped for the purpose of timber volume estimation, and those classes of interest in a wildlife habitat mapping program. Although there would be some common information needs satisfied by a general vegetation cover type map, the classes and their definition would diverge for each of these two specific mapping applications. In other words, the *purpose of the classification* can lead to the definition of classes that are more or less useful for the ecological monitoring application.

A summary of a few of these fragmentation, habitat and biodiversity studies and the classes that were presented in each is provided in Table 7.9. A common feature of these efforts has been the identification and production of remote sensing products, or lists of products, that consist of mappable phenomena which relate to the landscape biodiversity elements or wildlife habitat or fragmentation indices. For example, Imhoff et al. (1997) showed that SAR data could be used to discern three-dimensional structural differences in bird habitat quality, while multispectral imagery were useful in discriminating floristic differences in habitat type. In that mapping study of bird diversity, input variables ranged from measures of tree and canopy density to estimates of total biomass and volume. Coops and Catling (1997) used airborne videographic data (a very inexpensive form of remote sensing, see King 1995) to provide spatial context for a prediction of composition and abundance of faunal groups in an Australian eucalyptus forest. The spatial context was rendered in the form of a classification of structural percentiles for tree and shrub canopies, and several soil moisture classes. In the Chicago Wilderness regional biodiversity study, Wang et al. (1998) described classification protocols involving a range of imagery (Landsat, aerial photography, high spatial detail aerial digital cameras) and input variables (NDVI, classifications of rare natural communities). Central to their approach is the generation of classification systems that bridge the natural and urban environments.

Table 7.9 Classes used for fragmentation, habitat and biodiversity mapping at the landscape scale
B = Biodiversity; F = Fragmentation; H = Habitat
D = Disturbance; G = Geomorphology; LC = Land cover; S = Succession; SL = Soils; VG = Vegetation Structure

<table>
<tr><th colspan="2">Type of Mapping</th><th colspan="4">Class</th><th>Type of Study</th><th>Reference</th></tr>
<tr><td>F</td><td>LC</td><td>Forest</td><td>Non-forest</td><td></td><td></td><td>Rate and pattern of forest change</td><td>Zheng et al. 1997.</td></tr>
<tr><td rowspan="2">F</td><td rowspan="2">LC</td><td>Mixed-deciduous forest upland</td><td>Mixed-deciduous forest lowland</td><td>Pine forest upland</td><td>Pine forest lowland</td><td rowspan="2">Landscape fragmentation</td><td rowspan="2">Luque et al. 1994</td></tr>
<tr><td>Non-forest</td><td colspan="2">White-cedar swamps</td><td>Water</td></tr>
<tr><td rowspan="2">F</td><td rowspan="2">LC</td><td>Mesophytic forest</td><td>Riparian woodland</td><td>Secondary forests</td><td>Eucalyptus spp.</td><td rowspan="2">Forest fragmentation</td><td rowspan="2">Jorge and Garcia (1997)</td></tr>
<tr><td>Savannah</td><td>Pasture</td><td>Wetland</td><td>Barren land</td></tr>
<tr><td rowspan="2">F</td><td rowspan="2">D</td><td>Artificial regeneration</td><td>Fertilizer and herbicide</td><td>Grazing by livestock</td><td>Prescribed burning</td><td rowspan="2">Patterns of forest disturbance</td><td rowspan="2">Stapanian et al. 1997</td></tr>
<tr><td>Tree Species</td><td>Construction</td><td>Logging</td><td>Wildfire</td></tr>
</table>

		Richness	Disease	Insects	Weather		
F	LC	Woodland	Scrub	Orchard	Long grass	Vertebrate Habitat Disturbance in an Urban Environment	Dickman 1987
		Short grass	Allotments	Churchyards	Gardens		
		Vegetation Density	Total Vegetation Density	Vegetation Patchiness	Number of Plant Species		
		Time that patch has been undisturbed	Distance to buildings	Percentage of barren ground	Distance to water		
F	D	Forest	Open or bare	Shrub or successional forest	Distance from Road	Deforestation	Sader 1995
F	LC	Urban	Agriculture	Transitional	Water	Landscape fragmentation - Georgia	Turner and Ruscher 1988; Turner 1990
		Coniferous forest	Upper deciduous forest	Lower deciduous forest	Improved pasture		
F	LC	Clearcuts	Roads	Lodgepole Pine	Herbaceous	Forest fragmentation due to logging	Tinker et al. 1998
		Spruce/Fir	Douglas-fir	Sagebrush	Streams		
		Riparian willow	Mixed conifer	Blowdowns and burns	Riparian wetland		
		Ponderosa Pine	Riparian conifer	Rock and snow	Mountain mahogany		
		Juniper	Aspen	Cottonwood	Lakes		
F	D	Recent cut	Recent burn	Avalanch path	Old growth	Caribou Habitat	Deuling 1999
		Immature forest					
H	LC	Dense Conifer	Conifer	Mixed conifer	Deciduous	Bird Habitat	Venier and Mackey 1997
		Deciduous-regenerating	Topographic Wetness, DEM based				
H	S	Aspen age 0-12 year	13-25 year	26-38 year	38+	Grouse Habitat Suitablility	Rickers et al. 1995
H	VS	Elevation	Clearcut	Retention sites	Natural young	Bird Habitat	Hansen et al. 1995
		Commercial thin	Mean DBH	Natural mature	Old growth		
		Tree density by size class	Closed-canopy plantation		Variation in tree diameter		
H	SL	Soil wetness levels				Wading bird habitat	Avery and Haines-Young
H	LC VS	Spruce-fir	Ponderosa Pine	Mixed conifer	Canopy closure	GIS for red squirrel habitat modeling	Pereira and Itami 1991
		Meadow	Cienegas	Rock outcrops	Roads		
		Aspen	DBH	Aspect	Slope		
H	VS	Slope	Water %	DBH of trees	CWD cover %	Small mammal habitat	Carey and Johnson 1995
		CWD %	Large snags / ha	Moss %	Litter %		
		Forb-fern %	Low shrub %	Tall Shrub %	Canopy %		

H	LC	Sand	Water	Vegetation		Nesting habitat of two bird species	Sidle and Ziewitz 1990
B	VS	5 Non-forest	Conifer	Hardwood	Mixed	Landscape Structure, Habitat and Bird Diversity	McGarigal and McComb 1995
		Grass/forb	Shrub	Sapling	Pole		
		Small Sawtimber	Large Sawtimber	Open Canopy	Closed Canopy		
		Late Seral					
B	S	Open Canopy (<30 yrs)	Young (30-70 yrs)	Mature (80-190 yrs)	Old Growth (> 190 yrs)	Vertebrate Diversity	Hansen et al. 1993
B	D	Residual patches	Clearcuts without residual tree patches	Outside the residual patch but inside the clearcut	Edges of clearcuts	Bird Diversity	Merrill et al. 1998
B	LC	Palustrine	Residential	Agriculture	Oak-heath	Modeling urban growth to assess future impacts on biodiversity	White et al. 1997.
		Lacustrine littoral	Commercial-industrial	White Pine-hardwoods	Lacustrine limnetic		
		Hemlocks	White Pine	Shrublands			
		Sugar Maple-Red Oak	Sugar Maple-Ash-Basswood				
B	LC	Treed communities	Sloped (>5%) grasslands	Valley grasslands	Cultivated - disturbed	Preservation of Grassland Vegetation	Hall-Beyer et al. 1995.
		Eroded areas	Shrub (>15%)	Upland grass			
B	G	37 Soil types	9 Soil drainage types	5 Soil depth classes	5 Slope classes	Forest biodiversity	Burnett et al. 1998
		8 Aspect classes	7 Texture classes each for A and B horizons	Shrub species richness	Tree species richness		
B	G	Non-native plant species (disturbance indicators)	14 Soil drainage classes	16 Plant community classes	5 Slope classes	Landscape level biodiversity	Nichols et al. 1998.
			9 Aspect classes	Plant species richness			
B	VS	No. of trees /100 sq. meters	Bird species richness	Mean bole surface area / volume (SA/V)	Mean bole volume	Bird habitat and diversity	Imhoff et al. 1997.
		Mean height	Mean total branch volume	Mean branch SA/V	Total dry biomass		
		LAI	Mean DBH				
B	LC D	Alpine	Forest	High Alpine	Sub-alpine	Butterfly and bird diversity	Debinski and Brussard 1992
		Alpine with Riparian	Hydric Meadow	Xeric Meadow	Mesic Meadow		
		Trail	Disturbed				

B	H	4 Tree canopy (%) classes	4 Shrub canopy (%) classes	4 Ground herbage density classes	4 classes % of Logs, rocks, debris, etc	Fauna diversity prediction	Coops and Catling 1997
		4 Soil moisture classes					

On a global scale, Nemani and Running (1996) have reconceptualized vegetation classification and structure mapping with a view to integrating remote sensing data. They devised a new classification system based on three input variables (permanence of above ground biomass, leaf longevity, leaf type or shape), and have commented (p. 345) that '*remote sensing is the logical technology for global vegetation measurement*'. The result is that natural resource mapping, in general, is moving away from mapping theoretical (historical) distributions with untestable, invalidated models that do not retain credibility, to a practical, data-driven description of the landscape that is the product of tested, validated and credible methods. Earlier, Graetz (1990) provided a similar commentary in a call for local, regional and global functional vegetation classifications based on remote sensing. As mentioned earlier, the GOFC project specifically states that actual cover rather than potential cover will be mapped (Ahern et al. 1998).

In this task of matching indicators and remote sensing products, the EOSD initiative of the CFS is the most recent and advanced Canadian example (Goodenough et al. 1998). Remote sensing products for inventory (Table 7.10) and indicators (Table 7.11) were presented with an assessment of the likelihood that they can be obtained solely or partially by remote sensing. Individual remote sensing products could be highly localized. For example, indicator product 7.1.1 (area and severity of insect attack) in Table 7.11 might include measures obtained by remote sensing classification which could be expressed as percent defoliation (Royle and Lathrop 1997) or measures obtained by relating a foliar biomass estimate to an NDVI statistic (Franklin and Raske 1994). If an airborne system were used, the product could be generated on an individual tree basis (Leckie et al. 1992). If current satellite systems such as Landsat were used, the most appropriate reporting mechanism would be a combined remote sensing/GIS stand map based on the existing forest inventory (Ekstand 1990, 1994).

Table 7.10 EOSD inventory products (from Goodenough et al 1998)

1	**Total forest area**
2	**Area by forest type**
4	**Forest types by protection status**
5	**Other wooded land** by protection status and type
7	**Area and percent of forest land managed primarily for protective functions** (watersheds, flood protection, avalanche protection, riparian zones)
8	**Regeneration and afforestation area by type**
9	**Area of surface water in forests**
10	**Forests undisturbed by man**
11	**Other wooded land** undisturbed by man
15	**Area available for timber production**
16	**Area converted to non-forest use**
17	**Area and severity of insect attack**
18	*Area and severity of disease infestation*
19	**Area and severity of fire damage**
20	**Area of forest depletion (harvest)**
21	*Area and percent of forest land with significant soil erosion*
22	*Total biomass by forest type, age, succession stage*
23	*Total volume of all species on timber producing land*
25	*Current volume growth of forest*

Table 7.10 entries in bold can substantially be met by remote sensing, whereas those in italics can only be met partially by remote sensing. It is assumed that remote sensing is combined with geographic information provided from other sources, such as our provincial partners. Remote sensing can not directly measure age. However, broad classes, such as mature and immature forest stands, can be identified by remote sensing methods.

Table 7.11. Indicator Products (from Goodenough et al 1998)

1.1.1	**Percent and extent, in area, of forest types relative to historical condition and to total forest area.**
1.1.2	**Percent and extent of area by forest type and age class.**
1.1.3	**Area, percent and representativeness of forest types in protected areas.**
1.1.4	**Level of fragmentation and connectedness of forest ecosystem components.**
2.1.1	**Area and severity of insect attack.**
2.1.2	*Area and severity of disease infestation.*
2.1.3	**Area and severity of fire damage.**
2.2.1	**Percent and extent of area by forest type and age class.**
2.2.2	*Percent area successfully naturally regenerated and artificially regenerated.*
2.3.1	*Mean annual increment by forest type and age class.*
3.1.2	**Area of forest converted to non-forest land use, e.g., urbanization.**
3.2.1	**Percent of forest managed primarily for soil and water protection.**
3.2.3	**Area, percent and representativeness of forest types in protected areas.**
4.1.1	*Tree biomass volumes*.
4.1.3	**Percent canopy cover.**
4.1.4	**Percent biomass volume by general forest type.**
4.1.7	**Area of forest depletion.**
4.2.1	**Area of forest permanently converted to non-forest land use, e.g., urbanization.**
4.2.2	**Semi-permanent or temporary loss or gain of forest ecosystems, e.g., grasslands, agriculture.**
4.4.2	*Participation in the climate change conventions.*
4.5.1	**Surface area of water within forested areas.**
5.1.1	*Annual removal of forest products relative to the volume of removals determined to be sustainable.*
5.1.2	*Distribution of, and changes in, the land base available for timber production.*
5.1.5	*Availability of habitat for selected wildlife species of economic importance.*
5.4.4	*Area and percent of protected forest by degree of protection.*

Bold and italic entries have the same meaning as in Table 1. These indicators will also be measured by EOSD.

An indicator product that could satisfy the reporting requirement for the indicator 4.1.7 (Area of forest depletion) might be constructed from input provided by remote sensing, including a modified supervised/unsupervised classification of clearcuts using multitemporal Landsat MSS and TM imagery (Cohen et al. 1998), and a second classification of partial harvest treatments using a combined aerial/satellite image change detection approach (Franklin et al. 1999). Indicator product 4.1.3 (Percent canopy cover) could be based on a linear regression equation calibrated for the main forest cover types in the area (Wulder 1998a). Alternatively, high spatial detail aerial imagery could be used to build a canopy cover model in specific sites that could be extended using spectral unmixing or geometrical/optical modelling to larger areas (Woodcock et al. 1997).

The EOSD is part of the Canadian Space Agency's Long-Term Space Plan III, and is one component of the Canadian Forest Monitoring System (CFMS) that combines EOSD and the NFI. Unspecified linkages to an existing national forest database and national forest and landscape monitoring systems are mentioned by Goodenough et al. (1998). Linkages might occur through a database warehouse and information system incorporating climate, soils, elevation and remote sensing data . The EOSD project will use the NFI national plot systems (on a 20 km grid) with aerial photographs (2 km by 2 km coverage) and multidate satellite remote sensing images, and hence is a viable partner or collaborator for the application of remote sensing to biodiversity monitoring in Alberta. The standardization and documentation of remote sensing products is a necessary step in the biodiversity monitoring program, and some of this work has already been accomplished for related monitoring objectives by the EOSD and NFI. Furthermore, the AFBMP may obtain significant efficiencies in sampling, image acquisition, and execution of field data collection, if a close relationship were to be maintained between the emerging remote sensing protocol and the existing plans for an NFI pilot study.

Developing a Remote Sensing Protocol

In a recent review and prognosis for remote sensing, Glackin (1998) observed that:
"*In the year 1998 we stand at the threshold of tremendous change in the international spaceborne remote sensing arena. Spatial and spectral resolution are scheduled to increase dramatically, the number of small remote sensing satellites is about to jump from a handful to many…The coming decade will witness a transition of the Earth remote sensing field from one which is dominated by large, complex, expensive civil government and military systems to one that includes an increasing number of purely commercial systems…and an emphasis on the production of end-user products… There are outstanding needs for graphical user interfaces, image processing software, image compression tools, image browse software, advanced computer hardware… trained scientists and engineers who can understand the data and bring an end-to-end systems perspective to the burgeoning field of Earth remote sensing… and for those in the user community to understand the technology…".*

The preceding introduction, review and assessment of the remote sensing and ecological perspectives on biodiversity monitoring has been organized and presented with a view to summarizing the necessary background information to enable insight into the emerging view that *remote sensing is an obvious practical way to monitor changes in biodiversity at the landscape scale*. A brief, though systematic, review of remote sensing image characteristics and image products was related to the current understanding of patches, the relationship between patches and biodiversity, metrics to capture essential landscape dynamics, and the emerging standardization in remote sensing products that are designed to answer specific needs for indicators or inventory measures. While remote sensing is narrowly considered to be the acquisition and analysis of measurements of multispectral reflectance or emittance, this is clearly only one aspect of the complex monitoring system that is required. They must also include field and GIS data, models, maps and interpretations. In order to monitor biodiversity in Alberta at the landscape scale using remote sensing, a common understanding and application of remote sensing must exist and must be documented carefully and completely. This is the form and function of a remote sensing protocol.

Issues in data acquisition, image processing, information system design and operation, and the increasingly technological future expansion of remote sensing must be considered in the development of a remote sensing protocol. One possible sequence of actions was suggested by Wulder (1998b) in his review of NFI remote sensing activities:

1. data collection (e.g., air photo data, satellite imagery),
2. data processing (e.g., radiometric estimation, change detection), and
3. information extraction (e.g., image classification, GIS data).

Within this grouping, specific details on individual tasks can be prescribed. For example, a standard image classification methodology might be documented that includes a list of hierarchical classes, spectral and textural descriptions of the input variables (the bands) to use, the classifier training methods, the actual decision rule, the accuracy assessment procedure, and so on. Based on this approach, with finer and finer divisions of tasks, the optimal approach in remote sensing in biodiversity monitoring could be broken down into discrete steps. When taken as a whole, this series of steps may form the basis for a complete remote sensing protocol.

A more detailed, though still broad, example of the possible steps in a complete remote sensing protocol would include:

- select or target individual ‘products’ from lists of potentially mappable biodiversity elements,
- acquire and process appropriate satellite and aerial imagery at multiple spatial resolutions to enable a scaling-up of image ‘products’ from feature-based individual objects to generalized time-series plots of global processes,
- devise and test a set of classes that can adequately characterize homogeneous patches and can represent patch dynamics over time within the selected ‘product’,
- collect and validate training field and GIS data to represent the variability within such classes,
- generate and apply statistically sound classification decision rules to the list of such classes for which the data are optimized (including per-pixel, mixel, texel and fexel image processing approaches),
- evaluate the performance of the classifier using an independent sample,
- determine an appropriate set of landscape metric factors (which might be optimally comprised of a multivariate selection of indicators such as fragmentation, connectedness, etc….),
- apply the preceding to several sites perhaps on a continuum of recently disturbed to mature, and compare results (such as stability of the metrics, sensitivity of reflectance to known differences in cover, APAR, etc.).

Reviewing each of these steps, with an understanding of the current capabilities of remote sensing technology to monitor specific landscape-level biodiversity elements (including, but not limited to, for example, vegetation patch size, shape and spatial arrangement), can lead to an understanding of the required input to a remote sensing protocol. For example, definitions of patch characteristics (i.e., differentiation, homogeneity, and so on) are essential before the selection of the appropriate remote sensing spatial resolution can be attempted. In a landscape monitoring exercise, virtually everything depends on the definition of a patch – traditionally, using low resolution satellite imagery, patches would be homogeneous areas of forest, water, rock; using medium resolution satellite imagery, patches would be similar to those that can be interpreted readily from 1:100,000 scale aerial photographs (e.g., conifers, deciduous, mixedwood stands of forest, two or three types of shrub and wetlands, etc.); using high spatial detail imagery, patches could be broken down into areas of sunlit tree crowns, shaded crowns, understory assemblages, and so on. With digital remote sensing, however, patches could be defined heuristically and empirically, on the basis of forest cover and structure but with reference to internal functioning of processes such as photosynthesis, environmental stress or damage.

In order to quantify individual organisms or patches that encompass individual objects (trees, shrubs, shadows, etc.) in a plot, higher spatial detail imagery processed with a feature-based strategy would be required. A major emphasis in this protocol would be the execution of the aerial mission to generate very high spatial detail imagery to a fixed standard for geometry and radiometry. If a monitoring program were aimed at homogeneous units of dominant/co-dominant species composition patterns, then a combination of high spatial detail and lower spatial resolution satellite imagery would be optimal. The low spatial resolution TM imagery could be used to characterize heterogeneity, and the high spatial resolution data could be acquired within the least homogeneous areas thus defined. Emphasis in this part of the protocol would be placed on the continuity of classification decision rules and (perhaps) signature extension through training data collection.

However, one major issue would be the existence or ease of acquisition for such imagery, and this might be tied to the existence of other Canadian monitoring programs (e.g., NFI, EOSD) and international strategies (e.g., GOFC). At the moment the Canadian NFI program appears to be largely based on aerial photography and aerial photointerpretation for patch definition at the landscape level. Since this does not appear likely to generate the optimal data set for biodiversity monitoring, some additional consideration of options for the AFBMP must be made. But, in many ways it is difficult, even counterproductive to compare a proposed digital method (i.e., complete image acquisition, processing, output using computer-based methods) to an existing aerial photointerpretation approach to landscape mapping. A completely digital method based principally on satellite imagery but including other image types does not yet exist. The EOSD program, which is Landsat TM-based, is under development with an important defining workshop underway at the time of this writing (March 1999 at CFS Pacific Forestry Centre). However, while there is an on-going methodological debate between aerial photointerpreters and digital image analysts, this discussion is essentially sterile in the context of the AFBMP. For monitoring biodiversity through repeatable, scientifically and statistically valid measurements, such as landscape fragmentation indices, a manual interpretation of patch boundaries and internal patch homogeneity is inconceivable in the future or even in the present (Frohn 1998). Does anyone really believe that the stand boundaries interpreted on aerial photographs in the last or next five years will mean anything in thirty years?

The concept of a forest stand as a unit in forest management planning itself has recently been reviewed (Holmgren and Thuresson 1997) in light of the increasing availability of computer methods (e.g., for volume estimates, a combination of circular plot inventory and remote sensing). These comments are not meant as a criticism of forest mapping and inventory procedures as Lowell and Edwards (1996) have pointed out, *"Given the uncertainty inherent in a forest relative to how it must be represented in a database, foresters have few alternatives."* Today an opportunity to design a new information gathering method - a new protocol aimed at forest biodiversity - exists, and more and better alternatives are now available. In the future, perhaps only a few years, even aerial photography will be acquired originally in digital formats and then converted to analogues for those who desire the traditional products (King 1995). In fact, there is increasing interest and activity in digitizing archived aerial photographs (Holmgren and Thuresson 1997), and processing the imagery with computer methods (Leckie et al. 1999) including some of those outlined in this chapter.

A more pressing concern is an intermediate step, the processing of satellite imagery using GIS databases (Lowell and Edwards 1996; Wang et al. 1998) which are often available from earlier aerial photo interpretations and which impose an unverifiable, elusive and often incorrect structure on the landscape. A few examples exist that show that the integration of remote sensing and existing data can lead to data and model synergy and to results that were not otherwise obtainable (e.g., Wolter et al. 1995; Franklin et al. 1997a,b). But what methods are best to combine the existing state of knowledge about the forest with the new view provided by satellite or aerial reflectance patterns? What field programs are needed to support the conversion of the inventory database (for that is usually what is available, perhaps something like the AVI) to something useful in interpretation and understanding of current and future remote sensing products? What algorithms can be improved, standardized, or replaced in automated image interpretations? What essential information in a remote sensing image continues to lie dormant, hidden, waiting to be revealed through scientific insight and innovative image processing?

Recommendations

General

A general outline for a remote sensing protocol for the AFBMP would include an understanding of the importance of the following issues and agreement on specific details:

- A selection of biodiversity elements and specific biophysical features which can be monitoring using remote sensing must be selected and prioritized from a candidate set of 'products',
- Digital imagery must form the basis for the development of remote sensing products to ensure data consistency and the understandable application of scientific methods,

- Imagery may be required for at least three general levels of spatial detail (low, medium, high resolution) for sample plots,
- Imagery at medium and low resolution may be required for the entire landscape,
- A hierarchical classification system is required for land-cover,
- The resulting database should have wide distribution and comprehensive application,
- Conceptually-simple and practically similar approaches to classification of these data are required across the sample design (standard methods of image preparation, georadiometric processing, specific decision rules, input data manipulations, and so on).

Remote sensing should be recognized as having a service role and a monitoring role in the larger program. The service role may consist of the production of detailed maps of the plots and surrounding landscape which can be used by all monitoring teams and which might contribute to understanding distributions of other monitoring elements. The use of remote sensing data as predictive variables within the monitoring role of remote sensing should be considered immediately, possibly to reduce expense and redundant field data collection. The monitoring role of remote sensing includes classification, biophysical parameter estimation, and change detection. However, landcover, patch homogeneity or even patch dynamics may be some of the last things to change in response to stress or disturbance. Perhaps we need to know more about the processes within and between patch boundaries, processes such as photosynthesis or respiration that are likely more sensitive to future conditions brought about by global processes such climate change. Identifying and quantifying these processes within the larger classification protocol is recommended.

An additional consideration might be to ensure that the remote sensing protocol can provide input to calculations of the carbon budget and is designed to be sensitive to carbon dynamics and modelling parameters. For example, accurate NPP estimation or modelling requires remotely sensed leaf area and cover type.

Logistical Considerations

A list of the long-term challenges that must be met to execute a monitoring program over the forested area of Alberta is required. What field data would be required? What sampling regime would be applied? What level of integration with the GIS would be required? What personnel and facilities would be required? This section is highly speculative, but based on the experience of the authors is worth documenting, if only to put an order-of-magnitude envelope around the execution of the emerging remote sensing protocol.

In all of the following estimates of cost and time, the total area to be considered is approximately 500,000 km^2 (the forested area of Alberta). The estimates are constructed with the assumptions that a maximum of 5,000 plots will be processed (once, over an undetermined amount of time).

Image Data Acquisition

The sampling design selected for the biodiversity monitoring program will affect the data acquisition costs; dramatic differences can be assumed in cost of imagery at different levels of spatial detail. One reasonable approach is to acquire imagery at sample plot locations at the highest spatial detail possible (with commercially available image suppliers, perhaps 0.5 m spatial resolution, 5 bands), and to provide all plots at an intermediate resolution (perhaps 1 m to 5 m spatial resolution, 15 bands), with inter-plot coverage at medium and low resolutions only (perhaps 10 m to 30 m spatial resolution, 5 bands, with satellites). The very high spatial detail plot-based remote sensing would require buying an external control and might cover an area up to approximately 10 km^2.

Typical image costs in 1998 were:

- Airborne digital sensor package \$10 per km^2
- SPOT satellite \$0.69 per km^2
- TM satellite \$0.14 per km^2
- IRS-1 (similar to SPOT)
- Radarsat (similar to TM)

Obviously, there would be a huge difference in cost to acquire remote sensing imagery if high spatial detail imagery were required only for a few plots, every plot, or even for interplot coverage. A multiple resolution image acquisition could be planned as part of a *hierarchical image acquisition strategy* within the remote sensing protocol. But, assuming full plot coverage at the highest spatial detail, then the following breakdown would be a realistic image acquisition framework:

- Airborne imagery for every plot at 10 km^2 per plot = \$100 X 5,000 (the number of plots); plus,
- Medium and low spatial resolution imagery for the entire province (wall to wall coverage of SPOT HRV, Landsat TM or Radarsat scenes, plus sampled areas covered by SPOT Pan or IKONOS or SPIN-2 scenes). Many of these already exist and only royalties might have to be paid for their use.
- Total Estimated Cost for Image Data Acquisition: approx. \$1,000,000.

Other Data Acquisition

Major expenditures in time and money would be incurred in acquiring data to support the remote sensing image acquisitions. For aerial remote sensing, these data acquisitions would include mission-specific observations of incoming light, deployment and spectrographic monitoring of calibration panels, and differential GPS programming (see Wulder et al. 1996). Satellite remote sensing imagery could benefit from a similar data acquisition plan, but are more robust (i.e., through the use of models for atmospheric effects). However, a minimum set of observations would be required at each field plot and for each image: GPS of the plots and key geometric locations for use in georeferencing tasks, field spectrometer, plot mensuration (e.g., dbh, height, age, crown closure, species), image training and accuracy assessment data, atmospheric profiles or pseudoinvariant object measurement.

Acquisition of GIS data (minimum would be AVI or equivalent coverage for each plot or a sample of plots such that a probabilistic algorithm could be generated to imply the required attributes – as in He et al. 1998). Coverage of areas between plots could be 'filled-in' with new remote sensing data and the procedure to relate those new data to the AVI or equivalent in the areas that were already mapped. A similar status would be accorded provincial DEM data; these data could be extracted from existing mapping databases, generated for each plot if necessary from aerial photographs or other stereoimagery, and interpolated with satellite data between plots to provide wall-to-wall coverage. A national data set at 1:250,000 may be used but the accuracy may be insufficient (for orthorectification purposes).

- Total Estimated Cost for Other Data Acquisition: \$500,000.

Data Processing

Radiometric and geometric processing requires pulling together the image data and the GPS, spectrometer, atmospheric data for each aerial and satellite dataset. Key processing steps would include georeferencing, reflectance mapping, and identification of plot centres and boundaries. High spatial detail imagery comes with a high price in terms of large area coverage; these data must be mosaicked and radiometrically controlled over the larger areas; for example, with multiple flight lines. Commercially available software currently exists for all of these tasks. Estimating the cost of processing the image data into a usable form for analysis could be based on a fraction of the original image acquisition costs. Typically, this fraction would be equivalent to about one-third of the original image acquisition costs.

- Total Estimated Cost for Data Processing: $500,000

Information Extraction

Image information extraction, through classification, continuous variable estimation, or change detection, can be accomplished with a sliding-scale of automation, but even using the maximum amount of automation in the computer processing, all of these tasks require considerable human input and high-level interpretation. Often, the same amount of effort is required in compiling classification training statistics for a single Landsat TM image covering hundreds of square kilometers, as for a series of flights using high spatial detail acquisition but covering only a few hectares. If the classification task is considered as one of the more obvious candidates in the protocol, a general estimate of 3 to 5 weeks is reasonable to accomplish the data to map transformation. Therefore, the cost of classifying a single remote sensing image could be on the order of $5,000. It seems reasonable to base the estimate of information extraction costs as roughly equivalent to the original image acquisition costs.

- Total Estimated Cost for Information Extraction: $1,000,000.

Software Development

Most, if not all, of the software required for the image processing and GIS activities already exists in commercial systems. However, in a program such as this, specialized software would almost certainly be required to ensure efficiency and standardization across the program. Some of the more obvious new software developments would be in the creation of macros, GUIs, image processing, customized algorithms, mapping output, database browsers/archives, and so on. An additional series of customized tasks would be needed to maintain order in the database and in the associated meta-data. A part-time programmer in support of the remote sensing protocol would also be available for similar work other elements of the monitoring program, such as database management of plot data.

- Total Estimated Cost for Software Development: $100,000.

Personnel Training

Personnel training in support of field programs for remote sensing, acquisition of remote sensing data, interpretation and analysis of remote sensing data, and GIS/mapping output and database management would be required. Some consideration would be needed of the offerings of training workshops/courses by conventional software vendors compared to university or college based training; presumably, efficiencies could be obtained by pooling technical training and by hiring generalists/specialists in the correct balance. A typical remote sensing course at the University of Calgary would cost approximately $500 per student for tuition and materials.

- Total Estimated Cost for Personnel Training: $100,000.

Total Estimated Cost for the Remote Sensing Portion of a Biodiversity Monitoring Program for Alberta: **$3,200,000**.

Suggestions for a Pilot Study

Developing a Complete Remote Sensing Protocol

The objective of a pilot study would be to develop a complete protocol for the use of airborne and satellite image data in support of a forest biodiversity monitoring program. The protocol would be comprised of the careful documentation and agreement on standardization that would emerge from the following major activities:

- Definition of the target elements to be monitoring using remote sensing; for example, agreement is needed on the actual characteristics of a patch,
- Development of an acquisition strategy for aerial and satellite image data at multiple resolutions and with the appropriate physical characteristics for the patch delineation task,
- Organization and implementation of a coincident field program in support of image acquisition and to verify remote sensing products,
- Documentation of all image processing methods, decision rules and processes to generate the required products with the desired accuracy, precision and confidence intervals, and
- Assessment of output formats and links to GIS database for data continuity and subsequent processing in support of other monitoring activities (e.g., the provision of stand and plot maps to other protocols and teams).

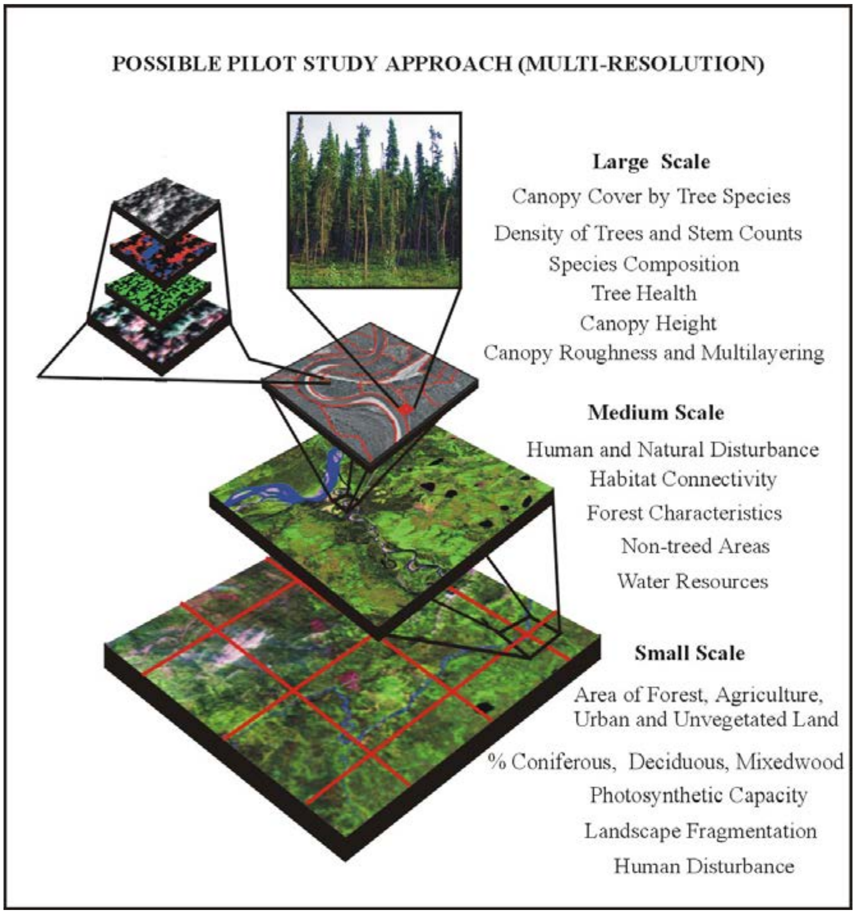


Figure 7.7 Possible pilot study approach (multi-resolution)

Testing a Complete Remote Sensing Protocol

The testing phase of a pilot study would involve the implementation and refinement, through iteration, if needed, of the major activities involved in developing the protocol. The outcome would be a report with examples specifying for the entire monitoring grid, the optimal image acquisition parameters, the appropriate definition of patches (by scale and method, see below), the classification structure and classes in the hierarchy to be used, a standardized decision-rule for the classifier, examples of the various ground observation forms, sample accuracy assessment calculations and sampling schemes, map design and database guidelines for maps, imagery, and metadata, recommended standards for image georadiometrics, mosaicking, time-series analysis, and so on. The tests should be organized to reveal the optimal methods and likely range of accuracy that could be expected in a monitoring program designed to provide landscape level analysis of features known to be of importance ecologically and yet practical within the constraints of the technology and the resources that might be available. An emphasis on three different functional issues in remote sensing might be reasonable:

1. Independently valuable landscape measurements (e.g., photosynthesis) and metrics (e.g., contagion, dominance, patch dynamics),

2. Measures to help set the landscape context (e.g., 3-dimensional spatial structure for ground plot surveys and variability in distributions),

3. Supplemental and/or replacement measures for some components of the ground sampling (e.g., plant structure and community).

Existing data sets in Alberta and methods which have received peer-review in the literature should be used to generate specific protocol information on a number of key possible elements. Some suggested elements below are provided for illustrative purposes only and would no doubt need refinement and logical testing across the full range of variability that must be sampled. They are listed here as specific examples of products in a biodiversity remote sensing protocol that could be generated in this pilot study timeframe (one year) and made available for discussion and approval in the larger monitoring program. A process of testing such individual products is recommended before a commitment to the complete protocol to implement remote sensing (at any scale) across the larger sampling system is required.

- Small-scale (large area covered, e.g., Natural Subregion, patch > 5 ha)
  - Area of forested, agricultural, urban, unvegetated land
  - Percentage of coniferous, deciduous and mixedwood forest
  - Photosynthetic capacity (NPP modelling, carbon budget dynamics)
  - Landscape fragmentation (a summary index)
  - Human disturbance (e.g., road density)

- Medium-scale (minimum patch approximately 0.5 ha)
  - Human and natural disturbance (e.g., forestry operations, seismic)
  - Habitat connectivity (a summary index)
  - Forest characteristics (composition, age class, crown closure, roughness)
  - Non-treed areas
  - Water resources (standing bodies, intermittent streams, wetlands)

- Large-scale (small area covered, feature-based, patch < 0.001 ha)
  - Canopy cover by tree species (gaps, snags)
  - Density of trees and stem counts
  - Species composition
  - Canopy height
  - Canopy roughness and multilayering
  - Tree health

<u>Outstanding Remote Sensing Questions</u>

Another aspect of the pilot study could be to select one element of the emerging remote sensing protocol in the biodiversity monitoring program and provide an exhaustive literature review and a comprehensive test using new or existing remote sensing data. Emphasis might be placed on specific research issues in working with the high spatial detail imagery, medium-scale landscape metrics, multitemporal change detection and backcasting, the integration of GIS and remote sensing for probabilistic model development, new classification decision rules, precise georadiometric properties of aerial imagery (such as bidirectional reflectance distribution functions), and so on. From such specific case studies of one or two images in one or two narrow applications, a protocol may emerge in a new area that would be available for standardization across the province.

For example, detection of patch dynamics remains an outstanding research question for many landscapes and patch definitions, but perhaps is most critical at the medium-scale (i.e., structural habitat units that are related to cover type, such as coniferous, deciduous, mixedwood, wetlands). One study could be designed to reveal the threshold below which landscape fragmentation at this scale cannot be detected with Landsat-type satellites. Can forest classes that are primarily related to successional patterns be detected reliably and with sufficient precision that changes in canopy dynamics within ecoregions would be detected? Can a classification scheme be used to stratify the landscape accurately enough for regression equations (e.g., between multispectral reflectance and stand volume or closure) to be developed within specific strata? Can measures of photosynthetic capacity (e.g., LAI) be related in a coherent way to human perceptions of patches that may be based primarily on species composition and structure? If so, can patch dynamics be represented more precisely with LAI-defined classes?

A different study could focus on the distribution of patches within traditional forest stands and would be primarily aimed at the larger scale questions that remote sensing might address. Can high spatial detail imagery (such as that available from SPIN or IKONOS satellites or aerial platforms) be used with coarser resolution imagery to scale individual tree information to the landscape level? What improvements in classification accuracy – and hence patch monitoring over time - can be obtained when using such high spatial detail information to help unmix coarser-resolution Landsat TM pixels? Can aerial remote sensing imagery be used to monitor gap dynamics and the changing photosynthetic capacity of stands subjected to insect damage or other disturbance? When considering the high spatial detail imagery more options are provided in terms of the questions that might be answered for specific landscapes and plots. Locations could be manipulated to produce the range of likely conditions (e.g., removal of overstory, partial removal of canopy, species selective mortality, understory assemblages, and so on).

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