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Remote Sensing for Forest Ecosystem Characterization: A Review

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1996

NODA • EDNO
CANADA
ONTARIO
Northern Ontario Development Agreement
Entente de développement du nord de l'Ontario
Forestry • Foresterie

Funding for this report has been provided through the Northern Ontario Development Agreement's Northern Forestry Program.

Canadian Cataloguing in Publication Data

The National Library of Canada has catalogued this publication as follows:

Treitz, Paul Michael, 1958–

Remote sensing for forest ecosystem characterization: A review

(NODA/NFP technical report; TR-12)
Includes an abstract in French.
"Funding for this report has been provided through the Northern Ontario Development Agreement's Northern Forestry Program."
Includes bibliographical references.
ISBN: 0-662-23600-9
DSS cat. no. Fo29-42/12-1996

1. Forests and forestry—Remote sensing.
2. Forest mapping—Ontario.
3. Aerial photography in forestry—Canada.
4. Forest management—Ontario.
I. Howarth, P.J.
II. Great Lakes Forestry Centre.
III. Title.
IV. Series: NODA/NFP technical report; TR-12.
SD387.M3T73 1996 634.9'2'09713 C95-980269-X

Catalogue No. Fo29-42/12-1996
ISBN 0-662-23600-9
ISSN 1195-2334

Copies of this publication are available at no charge from:
Publications Services
Natural Resources Canada
Canadian Forest Service–Sault Ste. Marie
Great Lakes Forestry Centre
P.O. Box 490
Sault Ste. Marie, Ontario
P6A 5M7

Microfiche copies of this publication may be purchased from:
Micro Media Inc.
Place du Portage
165, Hotel-de-Ville
Hull, Quebec J8X 3X2

Treitz, P.; Howarth, P. 1996. Remote sensing for forest ecosystem characterization: A review. Nat. Resour. Can., Canadian Forest Service–Sault Ste. Marie, Sault Ste. Marie, ON. NODA/NFP Tech. Rep. TR-12. 51 p.

ABSTRACT

Today, forests are viewed as more than just sources of timber. Although commercial timber production remains the primary use of Ontario's forests, their importance is currently recognized for a variety of nontimber values (e.g., recreation, wilderness, fish and wildlife, water, aesthetics, education, maintaining biodiversity, and regulating global climate). Thus, the forest has become a multiuse resource that requires an integrated forest site management approach to evaluate the biotic and abiotic elements of the ecosystem, as well as the ecological relationships within and between ecosystems. One of the objectives of this report is to provide a brief history of forest management in Ontario and to describe how it has evolved to recognize the importance of ecosystem elements and ecological parameters for an integrated, multiuse management approach.

A second objective is to review remote sensing methodologies that have been applied within a forestry context. Although ecosystem parameters are easily measured on the ground, detailed ecosystem mapping and monitoring of large tracts of boreal forest have proven elusive. Remote sensing offers potential for the mapping and monitoring of ecosystems at a variety of spatial resolutions (scales). During this review, the relationships between data collection and analysis techniques become a focus for successful forest information extraction from remote sensing data. As a result, the impact that spatial resolution of remote sensing data has on ecosystem information extraction is also discussed. Here, spatial resolution of remote sensing data is considered analogous to the scale of the observations, and is therefore viewed as surrogate for scale. This focus is particularly pertinent since the spatial resolution (scale) of remote sensing data for information extraction is currently an important research issue.

RÉSUMÉ

De nos jours, on considère les forêts comme plus qu'une simple source de bois. Bien que les forêts de l'Ontario soient surtout exploitées pour leur bois, on reconnaît maintenant leur importance à d'autres égards : loisirs, espaces naturels, faune (y compris le poisson), flore, eau, esthétique, éducation, maintien de la biodiversité et régularisation du climat planétaire. La forêt est donc devenue une ressource à usages multiples, et une approche d'aménagement intégré est requise pour évaluer ses éléments biotiques et abiotiques ainsi que les relations écologiques à l'intérieur des écosystèmes et entre les écosystèmes. Ce document a, entre autres, pour but de faire brièvement l'historique de l'aménagement forestier en Ontario et de décrire son évolution vers une approche d'aménagement intégré et polyvalent qui reconnaît l'importance des divers éléments des écosystèmes et des paramètres écologiques.

Le document a aussi pour objet d'examiner les méthodes de télédétection utilisées en foresterie. S'il est facile de mesurer au sol les paramètres des écosystèmes, la cartographie et la surveillance détaillées des écosystèmes sur de vastes étendues de la forêt boréale se sont révélées des tâches pratiquement irréalisables. La télédétection présente des possibilités pour la cartographie et la surveillance des écosystèmes à diverses résolutions spatiales (échelles). Nous mettons l'accent sur les rapports entre les techniques de collecte et d'analyse des données comme un aspect important à considérer pour l'extraction réussie de renseignements sur les forêts à partir des données de télédétection. En conséquence, nous examinons également l'incidence de la résolution spatiale des données recueillies par télédétection sur l'extraction de renseignements concernant les écosystèmes. Nous considérons la résolution spatiale des données de télédétection comme analogue de l'échelle des observations. Notre intérêt pour cet aspect est particulièrement pertinent, étant donné que la résolution spatiale (échelle) des données de télédétection pour l'extraction de renseignements est actuellement un domaine de recherche important.

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REMOTE SENSING FOR FOREST ECOSYSTEM CHARACTERIZATION: A REVIEW

INTRODUCTION

Although commercial timber production remains the major resource use of Canada's forests, additional demands on forested land now include nontimber values such as recreation, wilderness, fish and wildlife, water, and aesthetics. Forests are also becoming valued for education, maintenance of biodiversity, and regulation of the global ecosystem. An improved understanding of forest resources and the interactions among them is necessary to view these values in an integrated manner. Including these disparate demands within a truly integrated management system will require further development of forest resource databases (Forestry Canada 1990).

To achieve an integrated management system for the long term, detailed knowledge of the structural characteristics of the forest is required, complemented by an understanding of the relationships between those characteristics and the environment. Hence, there is a requirement to define the forest both from an ecosystem (unit) and an ecological (process) perspective. A wide variety of information can be accumulated from studying these characteristics and the relationships between them. This information needs to be organized and simplified in a manner that facilitates enhanced decision making at a variety of levels. From an ecological perspective, this organization has traditionally been done using quantitative analyses for classification.

A forest classification system must be based on ecological principles. For ease in applying the classification, it needs to be based on readily identifiable (or inferred) features of the land for easy identification in the field. In addition, use of an hierarchical classification system can support decision making at several administrative or geographic levels through the aggregation or disaggregation of the elements of the classification (Driscoll et al. 1984).

In this report the development of ecological land (forest) classification for Ontario is discussed, beginning with the pioneering work of G.A. Hills and colleagues on forest site characteristics. In his works, Hills stressed the physiographic characteristics of ecosystems since these are generally stable and largely in control of vegetation development (Burger and Pierpoint 1990). Hills' 'total site type' incorporated both the physiographic and biotic elements of ecosystems and provided the foundation upon which subsequent forest ecosystem classifications for Ontario would be based (Hills and Pierpoint 1960).

Detailed hierarchical forest ecosystem classifications have now been developed and implemented for large portions of northern Ontario (e.g., Jones et al. 1983, Sims et al. 1989). These hierarchical classifications are primarily designed for field-level mapping and consequently are difficult to implement for the large tracts of forested land characteristic of northern Ontario. They are also designed for mature forest stands (>50 years) and do not apply to recently disturbed or regenerating sites, or to other land-cover types within the boreal forest. Although climax or near-climax stands are likely to be more spectrally 'unique', climax stands alone do not provide managers with sufficient data to manage the forest for multiple uses. For truly integrated resource management, these additional components of the boreal forest need to be considered.

Remote sensing and digital image analysis techniques offer potential for assisting in the analysis of large forest tracts for identification of appropriate ecosystem classes, particularly within an hierarchical classification scheme. Remote sensing data are generally collected at a single spatial resolution whereas nature's elements exist at a variety of scales. It is difficult to identify a single spatial resolution (scale) of remote sensing data that will provide the most suitable level of information for extracting forest ecosystem characteristics. It is anticipated that multiscale remote sensing data will provide suitable information at a variety of levels for forest ecosystem classification.

In this report, the evolution of forest ecosystem classification is discussed in relation to site and stand characteristics. The role of remote sensing for ecological and forestry applications is also reviewed along with some of the major issues in digital image classification. As well, the issues of spatial resolution (scale) are discussed, particularly with respect to the relationship between surface features (i.e., objects and phenomena that contribute to spectral reflectance) and spatial resolution, and how this relationship affects classification accuracy. Spatial resolution is considered analogous to the scale of the observations (Woodcock and Strahler 1987) and will be used as a surrogate for scale (Csillag 1991, Lam and Quattrachi 1992).

FOREST RESOURCE MANAGEMENT

Recently, forest management has emphasized the need to understand and describe the ecological relations of forests. Treatment of Canada's forests in this manner provides additional information about the relationships between forests and their environment—information necessary for successful integrated resource management. This emphasis on ecosystems also provides a better understanding of forest contributions and/or responses to global environmental change. It is important that resource managers examine closely the factors that dictate how forests develop. These factors will vary across Canada, particularly with respect to climate, physiography, and soils. In addition, management practices will vary between provinces according to utilization pressures, data collection, and standards for forest management practices. The ecosystem approach is being adopted across Canada, as forest managers begin to examine forested lands from an ecosystem perspective (e.g., Klinka et al. 1979, Corns and Annas 1986, Stanek and Orloci 1987, Meidinger and Pojar 1991, Banner et al. 1993). The following sections briefly describe the evolution of information requirements for forest management from an Ontario perspective.

Forest Resources Inventory (FRI)

In the past, emphasis has been placed on managing Canada's forest resources for timber and fiber production. In response to managers' requirements regarding timber volume and yield estimates, an inventory of forest stands was implemented by the Ontario Department of Lands and Forests. This group established the Forest Resources Inventory (FRI) section within the Timber Management Division in 1946. One of the primary objectives of this inventory was to determine the total quantities and the locations of merchantable timber in the province by species and products. From a management perspective, the main concern at the time was that of sustainable yield.

In 1921, aerial sketching was introduced in Ontario as a means of forest mapping; the first aerial photography for this purpose was acquired in 1926. Over time, aerial photography, combined with ground sampling, became the basis for the FRI program. The first document outlining the forest resources inventory procedure for Ontario was published in 1960, with subsequent editions in 1965 and 1978 (Ontario Ministry of Natural Resources 1978). Of primary importance in the inventory is the measurement of parameters that are related directly to timber harvesting (e.g., volume estimates). To obtain general statistical data on forest stands, the forest is stratified using airphoto analysis techniques. Then, sufficient ground samples are located in each stratum to meet a predetermined level of accuracy within the stratum, and for the forested area as a whole (Ontario Ministry of Natural Resources 1978, Schreuder and Bonner 1987). Field-based and airphoto interpretation data are correlated to extrapolate statistics for similar stands not sampled in the field. Parameters measured in the field include species composition, basal area, age, height, site class, and stocking. Forest stands are classified for yield forecasting based on a 'site class' parameter (Plonski 1974), an expression of site quality determined by the height of dominant or codominant trees at a specified age (Bonnor and Morrier 1981). While this provides valuable information for estimating volume and forecasting yield, it is not satisfactory for prescribing harvesting and silviculture activities (Pierpoint 1986).

Vegetation Ecology: An Introduction

To manage forests effectively, the forest manager must have a thorough understanding of forest ecology and forest ecosystems. In response to this requirement, forest site information is becoming more vital for detailed management of forest tracts at both the regional and local levels (Bonnor and Morrier 1981). This section presents a general outline of forest ecology, followed by a brief description of forest ecology research in site classification for the boreal forest of northern Ontario.

Mueller-Dombois and Ellenberg (1974) describe vegetation ecology as:

> "the study of both the structure of vegetation and vegetation systematics. This includes the investigation of species composition and the sociological interaction of species in communities. It further includes the study of community variation in the spatial or geographic sense, and the study of community development, change, and stability in the time sense. Vegetation ecology is concerned with all geographic levels of plant communities, from broad physiognomic formations in the sense of biomes ... to the very fine floristic patterns occurring on an area less than a square meter in size. Vegetation ecology is very much concerned with correlations between environment and vegetation, and with the causes of community formation" (p. 9)

As defined above, the ecosystem approach to forest management deals with the composition, development, geographic distribution, and environmental relationships of plant communities. The emphasis in this paper focuses on vegetation systematics; that is, the classification of typical vegetation communities. However, vegetation systematics is no longer considered an end in itself, as environmental effects on vegetation development must also be considered. An ecosystem concept emphasizes this point in that an organism and its environment form a functional system in nature (Tansley 1935).

Ecosystems are defined based upon both structural and functional aspects (Mueller-Dombois and Ellenberg 1974). A forest ecosystem, then, can be described, in part, according to the vegetation of its component strata, e.g., tree layer, shrub layer, herb layer, and ground layer as defined by environmental factors such as climate, physiography, and soils. In addition, ecosystems are open systems that have inputs and outputs, and experience a specific set of responses and processes (Ovington 1962). The ecosystem concept cannot replace established vegetation and plant community concepts (Mueller-Dombois and Ellenberg 1974) as these are still necessary to characterize particular ecosystems in space (i.e., geographically) and over time. The ecosystem concept, however, emphasizes the need to consider all of those components that serve to define and functionally regulate ecosystems.

In classifying ecosystems, the vegetation ecologist aims to integrate vegetation and environment. Depending on the emphasis of the particular study, ecosystem boundaries can result from plant community boundaries (Sukachev 1945), soil or landform boundaries (Hills 1960), or by a combination of vegetation and environmental characteristics, as preferred by Rowe et al. (1961). The combined approach has been successful in providing ecological data for applied research in forest and site evaluation studies where the ecosystem components can be employed as indicators of the more transparent site factors, particularly for growth and yield studies (Mueller-Dombois and Ellenberg 1974). Ecosystem classification organizes the knowledge of particular environments, and provides a common scientific basis for the management of renewable resources (Klinka et al. 1980). This process must be initiated by a detailed examination of ecosystem site parameters.

Forest Site Characteristics

The Society of American Foresters has generally defined site as an area, considered as to its ecological factors and with reference to its capacity to produce forests or other vegetation; it is the ultimate expression of the combination of biotic, climatic, and soil conditions of a (usually) very localized geographic area (Society of American Foresters 1950). A site region has been characterized by Hills (1960) as a very broad geographic area in which the same vegetation succession will occur on the same physiographic site, providing the type and degree of disturbance are the same. This provides a management framework for the forester whereby silvicultural treatments will be relatively consistent. The four major descriptors of a site region are climate, physiography, vegetation (i.e., forest), and soil. All are closely interrelated, insomuch as change in one will impact the others (Fig. 1). Hills developed a series of site region maps for Ontario, initially defining seven regions based on temperature regime (Hills 1952), and later incorporating effective humidity to identify additional site regions (Hills 1958, Hills 1960). Forest species may occur in several ecoregions, but may exist in association with different physiographic conditions within different regions.

In a regional context, climate is one of the major factors affecting forest development, both directly and in relation to its influence on soil features and development, and on

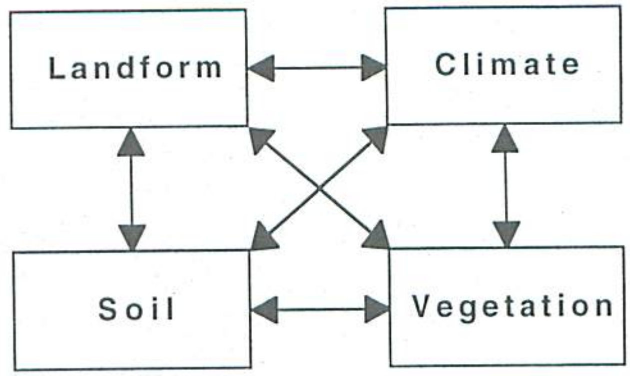

Figure 1. The four major descriptors affecting a site region.

topographic variables (e.g., insolation resulting from slope and aspect). At the site region scale, macroclimate is considered to be relatively uniform, since these regions are established by comparing natural successions of vegetation on similar landforms, rather than by using meteorological data (Hills 1960). The site region thereby is instrumental in forest management, since it represents an area that will respond similarly to natural disturbances and forestry practices within similar combinations of landforms and forest types (Hills 1960).

For the many interests incorporated into integrated resource management, a concept of site is required that can be tied to a common frame of reference. To achieve this, it is necessary to look upon site as a total environment; an integrated complex of all the features within a defined area (Hills 1952). However, Hills (1952) stressed that a site can be characterized by a select number of site components. Due to their stability, he selected physiographic features as the primary basis for representing a site.

The management of forest resources is also dependent upon a knowledge of the biological productivity of the land (Hills 1961). Ecological principles are used to rate physiographic sites for potential biologic productivity. Factors that affect forest growth are identified in Table 1. It must be remembered, however, that direct correlations between absolute levels of these factors and forest growth cannot be established since they are all interrelated, and the effect of each will vary according to changes in the other factors (Hills 1960). This knowledge of site provided the basis for determining the capability of areas for forest production (e.g., timber-use capability [Hills 1961]). This theme extended to the Canada Land Inventory and Ontario Land Inventory of the 1960s and 1970s (Department of Forestry and Rural Development 1965, 1966; Ontario Ministry of Natural Resources 1977). The purpose of these inventories was to collect a mass of information on the land's characteristics and to classify the land according to its capabilities in each of four sectors:

Table 1. Factors affecting forest growth.

Soil	Nutrient elements Toxic elements	Includes elements that are not nutritive or toxic, but control the degree of availability of nutrients to the plant.
	Soil moisture Soil aeration Soil structure Soil reaction (pH)	Many of these are directly related to the soil profile, while others are more closely related to broader land features (e.g., topography, geologic materials, and groundwater).
Climate	Atmospheric features	Includes atmospheric features, such as sunlight, heat, water, and carbon dioxide, supplied to the above-ground portion of the forest vegetation; provides mixing of oxygen, carbon dioxide, and heat to the organisms both above and below the soil surface.
Vegetation	Forest	Includes all the higher plants that synthesize material from sunlight.
Fauna		Includes all the animals that consume, either directly or indirectly, the products synthesized by plants.
Saprobes		The group of non-green organisms that reduce organic matter (e.g., micro-organisms, fungi).
Human		Human disturbance may be either (1) occasional and/or irregular (e.g., forest fire) or (2) sustained or regular (e.g., planned logging operations, silvicultural treatments).

(*Adapted from* Whittaker 1957, Hills 1960.)

agriculture, forestry, recreation, and wildlife. The limitations prescribed to assess forestry capability were climate, soil moisture, permeability and depth of rooting zone, soil fertility, toxicity, stoniness, and inundation (Department of Forestry and Rural Development 1966).

Ecological parameters that are important for silviculture include soil fertility, slope, soil texture, parent material, drainage, and aspect. With these parameters, it is possible to predict the type of regeneration and its potential growth (Levac 1991). These parameters can only be obtained through detailed examination of site type. Examination of the forest environment from this perspective provides a basis for the initiation of forest classification.

Land (Forest) Classification: The Canadian Perspective

Forests have been defined from two major perspectives: the geographic and the ecologic (Hills 1960). An example of the former includes Rowe (1972) based on Halliday's (1937) forest classification for Canada. The forest regions defined by this work are based on forest characteristics only, and even though climate and physiography may be described, strong ecological links between the forest and these factors are not implicit. The ecological approach to defining the spatial distribution of forests is based on ecosystem characteristics, structure, and function. These define the forest–environment relationships to provide a sound basis for forest management (Hills 1960), which can be applied at a variety of scales. In essence, the landscape is perceived as a series of ecosystems, variable in size and nested within one another in a spatial hierarchy (Rowe et al. 1961).

The Canada Land Inventory (CLI) was initiated in the early 1960s and provided the foundation for subsequent ecological surveys. It was a cooperative, federal–provincial program administered under the Agricultural Rehabilitation and Development Act (ARDA) of June 1961. The CLI represents a reconnaissance survey of land capabilities and uses (for forestry, agriculture, recreation, and wildlife) designed to provide necessary information for resource and land-use planning at the municipal, provincial, and federal levels. It was not designed as a management tool since it does not provide the detailed information required for management of individual parcels (Environment Canada 1978). Also, since it did not treat the various components within an integrated framework, it was not a true ecological classification (Karpuk 1978). For forestry, the objectives were directed toward providing a classification system rating the potential (productive) capability of the land under indigenous tree species growing at full stocking and under good management (Rees 1977). In Ontario, site regions as defined by Hills (1960) may be used as bases for the description of forest capability classes (Boissonneau et al. 1972).

The subsequent development of an ecological (biophysical) land classification in Canada was based on a need for baseline data for the interpretation of the Canada Land Inventory (Wiken and Ironside 1977). It was initiated in 1964 by the National Committee on Forest Land (NCFL), which established the Subcommittee on Biophysical Land Classification to study alternatives for a rapid, inexpensive approach to land survey. This subcommittee published guidelines outlining a methodology to classify and map ecologically significant units of land, as depicted by their inherent biological and physical characteristics (Wiken and Ironside 1977). These included parent material, landform, hydrology, vegetation, climate, and fauna (Wickware and Rubec 1989). The objective of this interdisciplinary survey was to map and describe ecologically distinct areas of the earth's surface at a variety of spatial scales. The resulting interpretive maps were based on biophysical and physical characteristics defining criteria at each level of generalization (Wickware and Rubec 1989).

Initially, a four-level biophysical land classification system was proposed to divide the natural environment into land units that were a combination of landforms and landform patterns, soils, and vegetation (Lacate 1969) (Table 2). Each land unit within a particular level is a more detailed subdivision of the previous level. Since this system was based on classification of vegetated environments, it was well-suited to inventories of forest and forest–tundra regions. These four levels of generalization were applied in a number of ecological land surveys (Gimbarzevsky 1978). The basic mapping unit was that of 'land type', which distinguishes an area by its surficial deposits. Forests were then mapped within each land type.

Over the last two decades, numerous ecological land surveys have been performed in a variety of environments

Table 2. Levels of generalization for ecological land survey.

Level of generalization Common scales of mapping	Definitions
Ecoregion Land region* Site region** 1:3 000 000 to 1:1 000 000	A part of an ecoprovince characterized by a distinctive ecological response to regional climate, as expressed by vegetation, soils, water, and fauna; characterized by regional climate reflected in the vegetation, but is heterogeneous in terms of other ecological phenomena.
Land district* Site district** 1:1 000 000 to 1:500 000	Characterized by a distinct relief pattern, geology, geomorphology, and associated regional vegetation; range of parent materials.
Ecodistrict 1:500 000 to 1:125 000	A part of an ecoregion characterized by a distinctive pattern of relief, geology, geomorphology, vegetation, soils, water, and fauna.
Ecosection Land system* Land type** 1:250 000 to 1:50 000	A part of an ecodistrict throughout which there is a recurring pattern of terrain, soils, vegetation, water bodies, and fauna.
Ecosite Land type* Site type** 1:50 000 to 1:10 000	A part of an ecosection having a relatively uniform parent material, soil, and hydrology, and a chronosequence of vegetation.
Ecoelement 1:10 000 to 1:2 500	A part of an ecosite displaying uniform soil, topographical, vegetative, and hydrological characteristics (e.g., plant community).

(*Adapted from* Hills 1958, Lacate 1969, Karpuk 1978, Environmental Conservation Task Force 1981, Rubec 1983, Wiken 1986, Wickware and Rubec 1989.)

* Represent levels of generalization defined by Lacate (1969).

** Represent levels of generalization defined by Hills (1958).

within Canada. It was observed that Lacate's original four levels of generalization often proved inadequate and as a result these were modified to suit specific environmental conditions. For instance, Thie (1974) observed that Lacate's system was more land oriented than an integrated land and water system. As a result, the levels of generalization have evolved over the past 20 years. This evolution is not only in response to a range of different environmental conditions, but also to new mapping technologies that have become available over the last two decades, including remote sensing technologies (Legge et al. 1974). These levels of generalization are presented in Table 2. A summary of the major developments in forest classification is outlined in Table 3.

Forest Ecosystem Classification

The pioneering work of G.A. Hills and his colleagues in developing an ecological framework for recognizing and describing forest sites in Ontario, along with other landscape-level and stand-level studies, spawned the development of a series of forest ecosystem classifications (FECs) for northern Ontario. The goal of existing FECs is to permit the "accurate, consistent and practical description of forest ecosystems so that existing and new management knowledge can be organized, communicated and used more effectively" (Sims and Uhlig 1992, p. 68). Forest ecosystem classifications aim to contribute to the organization of silvicultural practices, and to knowledge about and the application of integrated forest management. The framework upon which FEC systems are based incorporates those components of forest sites that contribute to forest development (i.e., canopy and understory vegetation, soils, landform, general climatic regime, and regional physiography (Fig. 2) (Sims and Uhlig 1992). Studies that demonstrate the applicability of FECs to forest management include those by Towill et al. (1988), Racey et al. (1989), and Wickware (1989).

Forest ecosystem classifications are primarily intended to be applied at the stand level, and to provide information about those local forest stands, vegetation, soil, and site conditions that the forest manager requires to develop management plans and strategies. It is proposed that this field-level information be integrated with other scales of forestry and planning information (Sims and Uhlig 1992). The basic units of FECs are Vegetation Units and Soil Units, which are determined through a "key" system (Sims et al. 1989) (Fig. 2). To adapt to a broader level for certain management purposes, these field-level units can be integrated to create ecological units (Hills and Pierpoint 1960), which are also termed operational groups (OGs) (Jones et al. 1983), treatment units (TUs) (Sims et al. 1989), or site types (STs) (Merchant et al. 1989) (Figs. 2 and 3). These aggregations of FEC soil and vegetation types possess similar species composition, productivity, and macroclimatic or ecological properties (Racey et al. 1989), and can be used with existing forest management knowledge to improve management interpretations and decisions (Sims and Uhlig 1992) (Figs. 2 and 3).

Forest ecosystem classifications have been completed for the Clay Belt (Jones et al. 1983), for northwestern and north central Ontario (Sims et al. 1989), and for sites supporting red pine (*Pinus resinosa* Ait.) and white pine (*P. strobus* L.) stands in the Algonquin Region of central Ontario (Merchant et al. 1989). FECs are currently under development for the Central and Northeastern regions. An extensive FEC computerized database has been developed that incorporates detailed soil, site, and vegetation information from mature or harvestable forest stands. This database has been used to acquire a better understanding of the nature, distribution, and relationships of site and vegetation in northern Ontario (e.g., Baldwin et al. 1990, Sims et al. 1990, Sims and Baldwin 1991, Walsh and Wickware 1991).

There are a limited number of resource survey databases available in Ontario, each providing only a part of the information required for silviculture or integrated resource management (Sims and Uhlig 1992). A comprehensive summary of resource inventories for Ontario has been published by Pierpoint and Uhlig (1985). Some of these are outlined in Table 4, along with an interpretation of their overall ability to provide information for integrated resource management. Note that the FEC provides more information related to the forest stand and site, and is therefore a more amenable application to integrated resource management.

Summary

Forest information requirements in Ontario have evolved from primarily inventory data to integration of site and forest conditions for a more comprehensive approach to forest ecosystem characterization. The importance of describing a forest from a more holistic viewpoint has been recognized by resource managers as a requirement for integrated resource management. Although forest ecosystem classification cannot solve land-use problems, it provides a basis for improved forest productivity and integrated management at a time when forest resources are under increasing pressure (Klinka et al. 1980).

Forests of the future will be more planned, managed, and regulated in a conscious effort to maintain biological diversity and support a range of forest values, not just timber resources. At the same time, some areas will be more intensely managed for timber and fiber production (Forestry Canada 1990). It is proposed that these objectives can be achieved through the maintenance of ecosystems at

Table 3. An evolution of land classification in Ontario.

Reference(s)	Synopsis
Landscape level	
Halliday 1937	Produced the original work 'Forest Regions of Canada'; a comprehensive description of areal distribution of Canada's forests.
Rowe 1972	Revised the work of Halliday's 'Forest Regions of Canada'.
Hills 1952, Hills 1958, Hills 1960, Hills and Pierpoint 1960	Development of the 'Ontario Site Classification System'; an hierarchical classification that emphasized physiographic characteristics of sites and was organized as a multilevel framework for forest management.
Department of Forestry and Rural Development 1965, 1966	Stemming from the mapping techniques developed by Hills et al., the 'Canada Land Inventory' (CLI) was developed. It evaluated land capability across Canada at scales of 1:250 000 and smaller.
Ontario Ministry of Natural Resources 1977	Similar to the CLI, the Ontario Land Inventory (OLI) was developed as a land capability evaluation program for extensive portions of the province.
Lacate 1969, CCELC 1976	Also based on Hills' work, techniques were adapted for an extensive set of land-classification surveys conducted in northern Canada during the 1960s and 1970s ('Ecological Land Classifications'); these programs were intended to provided multiple-resource inventories of northern terrain or broad-area treatments at a regional or provincial level.
Wickware and Rubec 1989	'Ecoregions of Ontario' is a synthesis and integration of a wide range of environmental information for Ontario within the national ecological database framework developed by the CCELC since 1976.
National Vegetation Working Group 1990	The proposed "Canadian Vegetation Classification System" uses a combination of physiognomic, structural dominance, and floristics criteria in a seven-level hierarchy.
State of Environment Reporting (SOER) Group of Environment Canada, Ottawa, 1994	Ongoing activities of the SOER Group to develop a nationally acceptable set of Ecozones and Ecoregions based upon climate, physiography, vegetation, and broad soil/landform patterns; in Ontario, Hills' site regions are prominent in the definitions of main terrain units.
Stand level	
Hills et al. 1960 (*from* Sims and Uhlig 1992)	Examined forest succession patterns as they relate to physiography in the northern Clay Belt (soil moisture regime, depth to bedrock, landform, and humus types were recorded for each vegetation type).
Zoltai 1965, Zoltai 1974	Hills' approach was applied to an area in northwestern Ontario where 24 land types were identified based on geologic material, soil texture, soil depth, stoniness, and common overstories.
Jones et al. 1983	The first in a series of forest ecosystem classification (FEC) programs was completed for the northern Clay Belt.
Merchant et al. 1989, Sims et al. 1989	FEC completed for the Algonquin Region and northwestern Ontario; underway in other parts of the province.

(*Adapted from* Hills 1960, Rowe 1972, Sims and Uhlig 1992.)

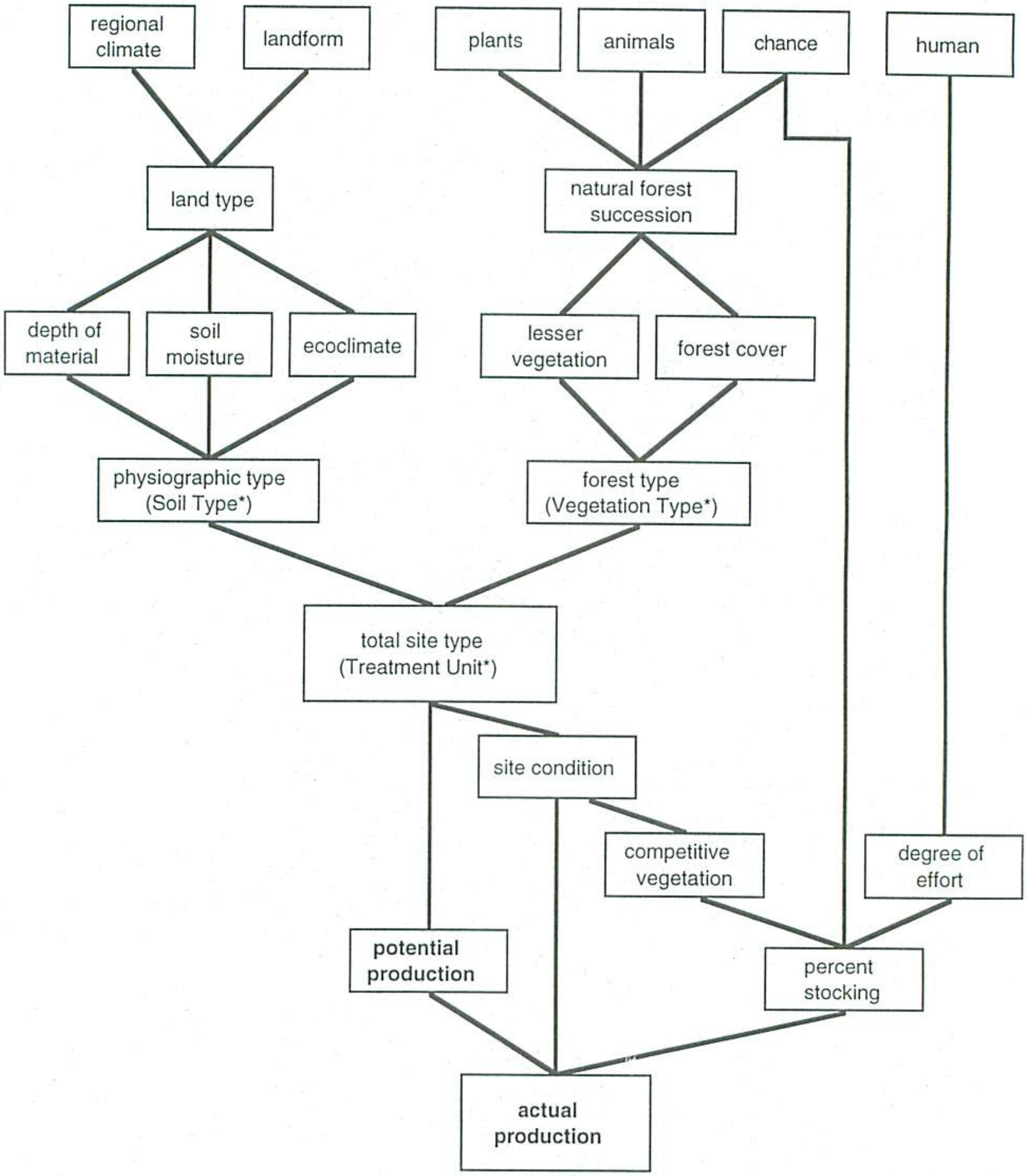

Figure 2. Ecological relationships determining forest production (Adapted from *Hills and Pierpoint 1960, Racey et al. 1989*).
* *Analogous terms for the NWO FEC* (from *Sims and Uhlig 1992*).

the landscape and stand levels. However, this can only be successful when forest resource managers have the necessary resource information need to effectively evaluate multiple uses.

REMOTE SENSING IN FORESTRY

Remote sensing is the science of deriving information about an object from measurements made at a distance. The quantity most frequently measured in present-day remote sensing systems is the electromagnetic energy emanating from objects of interest as opposed to other

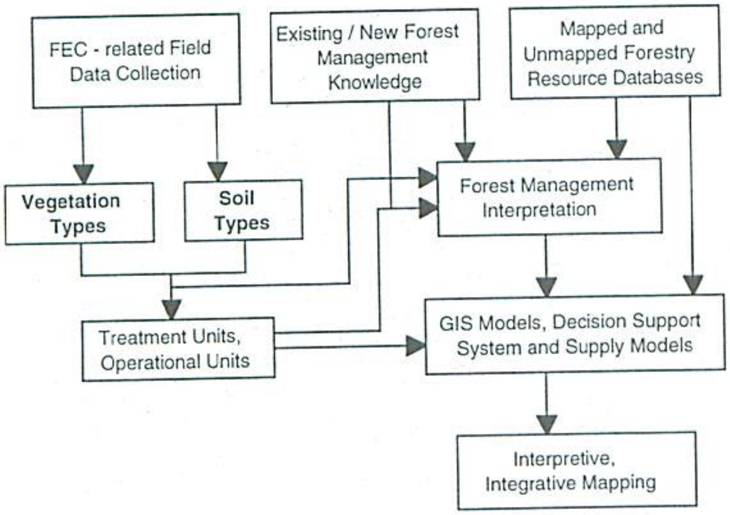

*Figure. 3 Organization of FEC soil and vegetation types (with the input of management information and knowledge; management interpretation may be developed iteratively (*from *Sims and Uhlig 1992).*

possibilities (e.g., seismic waves, sonic waves, and gravitational force) (D.A. Landgrebe, *in* Swain and Davis 1978). Remote sensing of electromagnetic energy in the visible and near-infrared portions of the spectrum at high and medium spatial resolutions (i.e., 1 m to 80 m) will be the primary focus of attention in the following sections. These are the primary data used for analysing vegetation at site and landscape scales.

Remote sensing in forestry can be divided into two major components: data acquisition (using sensors to record variations in the way earth's surface features reflect or emit electromagnetic energy) and information extraction (data analysis using visual or digital techniques). Both these components are closely related, in that the method by which remote sensing data are collected has a direct impact on the type of information that can be extracted. As a result, most remote sensing data are collected in a specific manner to optimize information extraction.

Remote Sensing of Forests

Remote sensing data used in forestry studies range from coarse-resolution weather satellite data (>1km) to high spatial and spectral resolution data acquired with airborne sensors (≤10m). Medium- and coarse-resolution earth resources satellite data with spatial resolutions ranging from 10 m to 80 m provide large-area coverage and are suitable for measuring coarse biophysical parameters or for segmenting the forest into general forest types. Meanwhile, high-resolution airborne and satellite remote sensing data (i.e., spatial resolutions ≤10m) are primarily used in specific case studies or for research where detailed information on forest stand and structural characteristics is examined.

Satellite Remote Sensing

With the launch of the first Earth Resources Technology Satellite (ERTS-1) in 1972 (later renamed Landsat-1), a new era began with respect to land resource mapping. Never before was systematic, repetitive, medium-resolution (i.e., 80 m) multispectral data available for the earth's surface. The Multispectral Scanner (MSS) has been carried by each of the five satellites launched in the Landsat series to date. Landsat-4, launched in 1982, carried a second scanner, the Thematic Mapper (TM). Currently, Landsat-5 carries both of these multispectral scanners. The Landsat program has provided data for over two decades and Landsat-5 continues to be in operation. The spectral, spatial, and temporal characteristics of Landsat sensors are outlined in Table 5. In 1986, France launched the first of a series of earth-observation SPOT ("La Système Pour l'Observation de la Terre" ["Earth-Observation System"]) satellites. These satellites incorporate linear-array detectors[1] to acquire data at higher spatial resolutions than does Landsat (Table 5).

A number of studies have been carried out to compare data acquired from different satellite sensors used in forest research. Lulla (1983) provides a useful summary of studies where Landsat MSS data were used for vegetation analysis and mapping. In comparing Landsat MSS and TM data for forest-species identification, Evans and Hill (1990) found that TM performed slightly better than did MSS for discriminating among pine species, but it was not significantly better for separating pine and hardwood stands. However, Williams and Nelson (1986) achieved a 20 percent improvement in the mapping of detailed Level III (Anderson et al. 1976) forest cover with TM data as opposed to MSS. This is the most detailed level of

[1] Linear arrays normally consist of a series of charge-coupled devices (CCDs) positioned end-to-end. Each detector element is dedicated to sensing a defined range of electromagnetic energy for a single ground resolution cell along any given scan line. The data for each scan line are electronically complied by sampling each element along the array (Lillesand and Kiefer 1994). This technology eliminates the need for a rotating mirror to scan across the ground surface, thereby increasing the amount of time that electromagnetic energy can be collected by a detector element.

Table 4. An estimate of the abilities of existing resource inventories in Ontario to meet some of the information requirements for integrated resource management.*

	FRI	FEC	Agriculture soil survey	OLI	SO/NO EGTS
Planning horizon					
Short-med. term (1–5 yr.)	XX**	XX	X	X	X
Long-term (5–20 yr.)	XX	XX	XX	XX	XX
Normal scale/resolution	1:20 000	Ground-based	1:10 000 (variable)	1:250 000	1:100 000
Extent of coverage in Ontario	Widespread	Local surveys	Scattered (small areas)	Widespread	Widespread
Species composition	XX	XX	O	O	O
Working group	XX	X	O	O	O
Stand density and spacing	XX	X	O	O	O
Present productivity	XX	XX	O	O	O
Potential site quality	O	XX	XX	X	X
Product type/product amount	X	X	O	O	O
Noncommercial forest types	X	X	X	O	O
Depth of mineral soil	O	XX	XX	X	X
Depth/type of organic matter	O	X	XX	X	X
Soil moisture regime	O	XX	XX	XX	X
Soil texture	O	XX	XX	XX	XX
Macro/microtopography	O	X	XX	X	X
Surficial geology/landforms	O	X	X	X	XX
Wildlife browse prediction	O	XX	X	O	O
Fisheries concerns	X	X	XX	X	XX
Competition prediction	O	XX	X	O	O
Windfirmness	X	X	X	O	O

* FRI = provincial Forest Resources Inventory (Obsborne 1989); FEC = Forest Ecosystem Classification; OLI = Ontario Land Inventory (Ontario Ministry of Natural Resources 1977); SO/NO EGTS = Southern Ontario - Northern Ontario Engineering and Terrain Survey Maps (e.g., Mollard and Mollard 1981).

** (O = not useful, X = useful, XX = very useful). (*From* Sims and Uhlig 1992.)

Anderson et al.'s (1976) land cover / land use classification system for use with remote sensor data (1:20 000–1:80 000 scale). Bradbury et al. (1985) compared Landsat MSS and TM data for classifying woodland and other land-cover types for an area in South Wales. It was found that TM data achieved 90 percent classification accuracy for woodland and provided suitable accuracy levels for identification of some tree species. In a similar study using MSS and simulated TM data over an agricultural area, Badhwar et al. (1984) found that although there was a decrease in mixed pixels at field boundaries, there was an increase in within-field variability, which may lead to poorer classification results. Horler and Ahern (1986) found the middle-infrared bands of Landsat TM to be particularly useful for analyzing stem density of coniferous forests, especially for forest regeneration sites in northwestern Ontario.

In comparisons of Landsat TM and SPOT multispectral (XS) data for biophysical analysis, Ripple et al. (1991) determined that the near-infrared bands of both sensors had strong negative correlations to the logarithm of softwood volume (XS 3, $r = -0.89$; TM 4, $r = -0.83$). In addition, Ripple et al. (1991) determined that XS and TM data sets exhibited high band-to-band correlations. In a similar study of forest inventory parameters, Brockhaus and Khorram (1992) found that TM data were more likely to be significantly correlated with stand parameters, such as basal area and age class, than was SPOT data. When equivalent bands of the two sensors were used to classify six forest classes and one water class in scenes from North Carolina, SPOT achieved slightly better accuracy (74.4 percent versus 70.8 percent). However, when all TM spectral features were included in the classification process, overall accuracy increased to 88.5 percent. This

Table 5. Earth resource satellite systems.

Sensor	Spectral range (mm)	Number of spectral bands	Spatial resolution (m)	Temporal resolution (days)
Landsat				
Multispectral Scanner (MSS)	0.5–0.6	4	80	16
	0.6–0.7		80	
	0.7–0.8		80	
	0.8–1.1		80	
Thematic Mapper (TM)	0.45–0.52	7	30	16
	0.52–0.60		30	
	0.63–0.69		30	
	0.76–0.90		30	
	1.55–1.75		30	
	2.08–2.35		30	
	10.4–12.5		120	
SPOT*				
HRV (XS)	0.50–0.59	3	20	26
	0.61–0.68		20	
	0.79–0.89		20	
HRV (P)	0.51–0.73	1	10	26

* SPOT consists of two identical High Resolution Visible imaging systems—each of which can operate in either three-band multispectral mode (XS) or single-band panchromatic mode (P).

Pointable optics (through a range of +/- 27° off-nadir) provide potential for increased temporal coverage.

(*Adapted from* Lillesand and Kiefer 1994.)

would indicate that the spectral resolution of TM is more important than the improvement in spatial resolution that SPOT XS provides. The importance of the additional spectral bands of TM (e.g., mid-infrared) for discriminating ground features has been confirmed for other sites with different environmental conditions (Nelson et al. 1984, Williams and Nelson 1986, DeGloria and Benson 1987, Chavez and Bowell 1988, Franklin and Wilson 1991, Joria et al. 1991).

Airborne Remote Sensing

Airborne remote sensing systems present a versatile alternative to spaceborne satellite systems. Airborne systems are flexible with respect to data acquisition parameters (e.g., time of acquisition, frequency of coverage, and spatial resolution). As a result, they provide the best opportunity to collect data that are optimal for extracting specific forest parameters of interest to the user (e.g., damage assessment during insect infestations, monitoring regeneration, and analysing forest structural parameters). However, the optimal conditions for data collection are not readily known. In addition, certain characteristics of high spatial resolution data (e.g., spectral variability, bidirectional reflectance) have confounded efforts to extract forest information digitally from remote sensing data. Details of forest stand structure (e.g., density, crown closure, understory) create a very complex mosaic of spectral reflectance values at high spatial resolutions. A review of remote sensing studies using airborne multispectral scanners and imaging spectrometers is presented below. An emphasis is placed on Canadian sensors and studies.

Multispectral scanner (MSS) data acquired from aircraft can be used as a primary source of information, as supplemental data to support more extensive satellite surveys or to provide a testing ground for proposed satellite sensors. Numerous forestry applications for airborne multispectral scanners can be found in the literature. For example, airborne MSS have been used for forest studies on a stand (Teillet et al. 1981, Irons et al. 1991, Franklin et al. 1991, Miller et al. 1991) and single-tree basis (Hughes et al. 1986, Yuan et al. 1991), and for estimating biophysical parameters such as biomass (Jensen and Hodgson 1985), green leaf-area index (Curran and Williamson, 1987), and forest-stand parameters (e.g., tree height, crown closure, tree and stand vigor, stand age) (Butera 1986, Danson, 1987). Measurements of these parameters may then be used to model additional stand characteristics such as basal area and volume (Smith 1986, Hall et al. 1989). For example, three canopy-closure classes (0–25, 25–75, and 75–100 percent) were modeled using Thematic Mapper

Simulator (TMS) data with prediction accuracies of 71, 74, and 57 percent, respectively (Butera 1986). Two airborne sensors, both developed in Canada, have contributed significantly to forestry research and are worth discussion. These are the Multi-detector Electro-optical Imaging Sensor (MEIS) and the Compact Airborne Spectrographic Imager (CASI).

The MEIS was developed in the late 1970s and early 1980s by MacDonald, Dettwiler and Associates (MDA) under contract to the Canada Centre for Remote Sensing (CCRS) to assist in the evaluation of linear-array technology and to develop remote sensing applications for this technology (Neville et al. 1990). The MEIS became the primary sensor of the CCRS electro-optical facility before being handed over to the private sector for operation. The MEIS is a high-performance digital multispectral imager that incorporates a linear-array design to improve radiometric[2] and geometric fidelity in comparison to traditional opto-mechanical multispectral scanners and survey cameras (Till 1987). The MEIS is an 8-channel imager, with the capability of incorporating a variety of lens and filter combinations, including continuous for–aft stereo acquisition. Detailed descriptions of the MEIS can be found in Zwick et al. (1978), Zwick (1979), McColl et al. (1983), and Till et al. (1983).

Airborne multispectral scanners have been used for identifying areas of eastern spruce budworm (*Choristoneura fumiferana* [Clem.]) damage (Ahern et al. 1986), and for improved estimation of insect damage on a per-tree basis as compared to conventional color infrared photography (Kneppeck and Ahern 1989). They have also been used successfully in discriminating tree species using principal components analysis (Leckie and Dombrowski 1984), evaluating forest regeneration (Brand et al. 1991), and assessing spruce budworm damage on a stand (Ahern et al. 1991a) and single-tree basis (Leckie et al. 1992). Treitz et al. (1992) reported variable results for identifying detailed ecological classes using 5-m resolution MEIS data in conjunction with a parametric classifier. These variable classification accuracies were attributed to the large spectral variance of forest stands caused by heterogeneous canopies at that resolution.

To date, satellite data have provided relatively poor spatial, spectral, and temporal resolutions for the detailed study of forest-stand dynamics. Even with airborne multispectral scanners, remote sensing data collection is limited to a specified and finite number of spectral bands. However, in the past decade, imaging spectrometers have been developed to acquire continuous spectra over land and water surfaces. These include the Airborne Imaging Spectrometer (AIS) (Vane et al. 1984), Advanced Solid-State Array Spectroradiometer (ASAS) (Irons et al. 1991), Airborne Visible-Infrared Imaging Spectrometer (AVIRIS) (Vane et al. 1987, 1993), Fluorescence Line Imager (FLI) (Borstad et al. 1985), Compact Airborne Spectrographic Imager (CASI) (Babey and Anger 1989, Borstad et al. 1989), and the proposed Shortwave Infrared Full-Spectrum Imager (SFSI) (Neville and Powell 1992). Research into the development of these airborne sensors and analysis of high spectral resolution data (Gaö 1993, Kruse et al. 1993) will provide a background for development of spaceborne imaging spectrometers for the Earth Observing System (EOS).[3] Some potential sensors are the Moderate Resolution Imaging Spectrometer (MODIS) (Ardanuy et al. 1991), the High-Resolution Imaging Spectrometer (HIRIS) (NASA 1987, Goetz and Herring 1989) and the European Space Agency's proposed Medium-Resolution Imaging Spectrometer (MERIS) and High-Resolution Imaging Spectrometer (HIRIS) (Iantosca et al. 1992). The development of high spectral resolution imaging spectrometers will permit improved study of those narrow-band spectral reflectance features that are characteristic of specific vegetation canopies.

Through field and laboratory studies, a variety of these narrow spectral band features have been shown to be related to changes in vegetation condition and amount. These include physiological characteristics such as chlorophyll amount and/or type (Horler et al. 1983; Rock et al. 1988, 1994; Vogelmann et al. 1993) and canopy chemical characteristics and their relation to carbon cycling (Peterson et al. 1988; Wessman et al. 1988, 1989). High spectral resolution sensors can also be used in the study of bidirectional reflectance characteristics of forest canopies (e.g., Abuelgasim and Strahler 1994, Ranson et al. 1994). An understanding of these characteristics is essential for the

[2] Radiometric fidelity refers to the sensitivity of a sensor/detector to detect subtle changes in energy flux at the surface that is being sensed. For digital sensors, radiometric resolution generally refers to the range of digital values that a sensor will record for any given surface (e.g., 8 bit or 256 grey levels).

[3] The Earth Observing System (EOS) is one of the primary components of the NASA-initiated concept Mission to Planet Earth (MTPE). The MTPE is an international earth science program aimed at providing the observations, understanding, and modeling capabilities needed to assess the impacts of natural events and human-induced activities on the earth's environment. EOS is the centerpiece of NASA's contribution to the program. It includes a series of polar orbiting platforms for long-term global observations, operated in concert with poplar-orbiting and midinclination platforms developed by Europe and Japan. The EOS is envisioned to begin in 1998 and continue for at least 15 years (*from* Lillesand and Kiefer 1994).

correlation of remote sensing measurements with biomass, species composition, stand structure, and reflectance.

Imaging spectrometry data, in conjunction with suitable analysis techniques, may provide a basis for quantitatively measuring phenological change in vegetated terrain that results from changes in primary productivity and vegetation vigor. The phenological changes may be in response to regional- and/or global-scale environmental or climatic changes (Miller et al. 1990a). Two assumptions must be satisfied if imaging spectrometry is to be useful in the biophysical analysis of terrestrial ecosystems (NASA 1987). First, there must be a strong correlation between canopy characteristics and the rates at which processes important to the biosphere occur. Second, these canopy characteristics must be successfully measured using high spectral resolution remote sensing data. Miller et al. (1990a) identified the most significant biogeophysical parameters that can affect plant vigor and primary productivity in terrestrial ecosystems as (i) leaf chlorophyll content, (ii) photosynthetically active radiation (PAR), (iii) canopy water content, and (iv) soil nitrogen content. The authors proposed that it is possible to derive chemical and morphological characteristics from a variety of spectral reflectance parameters that can be measured using various remote sensing tools. These include the measurement of red-edge[4] spectral position (Horler et al. 1983; Rock et al. 1988; Boochs et al. 1990; Miller et al. 1990b, 1991; Elvidge et al. 1993; Vogelmann et al 1993), normalized difference vegetation index (Tucker et al. 1986), moisture stress index (Cohen 1991), and shortwave infrared reflectance parameters related to canopy chemistry parameters (Peterson et al. 1988; Wessman et al. 1988, 1989). Further examples of the use of remote sensing data in biophysical studies are discussed later (*see* Biophysical Remote Sensing).

The FLI, also known as the Programmable Multispectral Imager (PMI) and CASI systems have contributed a great deal to the development and future of imaging spectrometry technology in Canada (Gower et al. 1992, Staenz 1992). Both systems are able to collect data in two modes: spectral mode, where continuous spectra for ground resolution elements are collected for up to 288 spectral bands; and spatial mode, where a more limited number of spectral bands is recorded, but complete spatial coverage for the swath is provided (Table 6).

The FLI was designed as a prototype instrument for the federal Department of Fisheries and Oceans, primarily to map ocean and coastal phytoplankton concentrations by imaging the emission from solar-induced fluorescence of chlorophyll a (Gower et al. 1992). Although the FLI was applied mainly to mapping of chlorophyll fluorescence and bathymetry, some terrestrial studies were also performed, particularly the detection and monitoring of chlorophyll red-edge spectral characteristics and associated responses to stress (a shift towards the shorter wavelengths known as the "blue shift") (Rock et al. 1988, Gower et al. 1989).

The CASI has been involved in a number of forestry studies with encouraging results. Representative studies include measuring vegetation red-edge parameters (Miller et al. 1991), recording spectral signatures for tree species (Gong et al. 1992b), determining surface reflectance anisotropy (Franklin et al. 1991), and identifying forest species and stand parameters (Franklin et al. 1991, Gillespie et al. 1992, Franklin 1994). Palmier and Ansseau (1992) used laboratory studies of spectra, specifically the red edge, to define spectral bands for CASI data collection to assess chlorosis and stress in sugar maple (*Acer saccharum* Marsh.). For forest-cover mapping, it has been demonstrated that high-resolution CASI data (2.5 m) were highly successful in discriminating lodgepole pine (*Pinus contorta* Dougl.), balsam poplar (*Populus balsamifera* L.), trembling aspen (*Populus tremuloides* Michx.), and cottonwood (*Populus trichocarpa* Torr. & Gray) without the addition of ancillary variables (Franklin et al. 1991). The authors also confirmed the variability of remote measurements of radiance as a consequence of topography and viewing-angle changes. This is a significant observation and underlies the importance of atmospheric corrections for application of remote sensing data in biophysical analysis and classification.

Forest Information Extraction

Remote sensing data can be used for a variety of applications in forestry. The following discussion examines uses of remote sensing for monitoring forest change and biophysical parameters, and for mapping and classifying forest stands.

Change Analysis

The repetitive, synoptic coverage of satellite, and to a lesser extent, airborne remote sensing systems provides for the monitoring of dynamic change in forest environments. This ranges from dramatic short-term changes (e.g., forest harvesting, fire, insect damage) to more subtle

[4] The red edge is the slope of a reflectance spectrum over the range 0.68 to 0.76 um. Shifts to longer or shorter wavelengths are used to document changes in the chemical or morphological status or health of plants. For example, trees stressed by high concentrations of heavy metals in the soils generally display a characteristic shift of the red edge toward shorter wavelenghts, often referred to as the blue shift (Lillesand and Kiefer 1994).

Table 6. A comparison of the Fluorescence Line Imager (FLI) and the Compact Airborne Spectrographic Imager (CASI) sensors.

Parameter	FLI	CASI
Spectral coverage	430 nm to 800 nm using 288 detectors; pixel size 1.3 nm; spectral resolution 2.5 nm	418 nm to 926 nm using 288 detectors; sampling interval 1.8 nm; spectral resolution 2.9 nm
Spectral mode	Spectra are recorded from 40 directions across the swath; bandwidth and look direction are under software control.	39 spectra of the full 418 nm to 926 nm range are recorded, with 2.9 nm resolution, from 39 different directions across the swath; a full-resolution image at a predetermined wave length is also recorded to assist in track recovery.
Spatial coverage	70° swath, 5 cameras, 1 925 detectors; spatial resolution 1.3 mrad	35.5° swath, with standard lens; single camera gives 612 pixels; sampling interval 1.2 mrad; spatial resolution 1.6 mrad
Spatial mode	Spectral pixels are grouped to form a pushbroom image about 1 900 pixels wide in each of eight spectral bands; band width and spectral position are under software control.	Spectral pixels are grouped to form up to 15 bands (512 pixels wide); band width and spectral position are under software control; the number of bands governs the integration time.

(*Adapted from* Gower et al. 1992.)

long-term changes in forest ecosystems (e.g., succession, growth/regeneration, primary productivity). In the latter sense, satellite data should prove useful for monitoring ecosystem responses caused by environmental change.

For monitoring change caused by harvesting or insect activity, temporal satellite data can be used to identify significant levels of forest canopy alteration. Initially, only changed versus unchanged canopies require identification (Nelson 1983). Once areas of change have been identified, more detailed sampling can be undertaken to define the nature of such changes. Landsat TM has become an operational tool for the identification of areas of dramatic change, usually caused by harvesting or fire. As a result, Landsat TM has been used to update large forest databases (Pilon and Wiart 1990, Maclean et al. 1992, Maus et al. 1992).

Insect, disease, and environmental damage to forest tree species has long been of primary interest to forest managers. Mapping and quantification of forests damaged by biotic and abiotic factors is crucial to managing forest operations, in particular for the planning of control or remedial programs. For instance, in 1985, the eastern spruce budworm (*Choristoneura fumiferana* Clem.) inflicted moderate and severe defoliation on 25.2 million hectares in eastern Canada, the Great Lakes States, and the northeastern United States (Leckie et al. 1988b). Early identification of areas affected by insect damage, and timely information on rates of spread/movement, in particular, are required as one component of a program to ensure the long-term viability of the forest industry in Canada.

Satellite sensing of insect damage is somewhat limited due to low spatial resolution, poor spectral characteristics, and restricted acquisition times of existing platforms (Nelson 1983, Rencz and Nemeth 1985), although more recent high spatial resolution satellites with pointable optics[5] (i.e., SPOT) have demonstrated some success (Franklin and Raske 1994). Efforts toward classifying levels of damage caused by spruce budworm have been mainly limited to airborne systems (Ahern et al. 1986, Leckie and Ostaff 1988, Ahern et al. 1991a).

Leckie (1987) has provided a useful review of the factors affecting defoliation assessment using airborne MSS data and of the problems encountered. Research examining the spectral characteristics of cumulative damage caused by spruce budworm, leading to selection of optimal sensor spectral bands, has been carried out by Leckie et al.

[5] Pointable optics provide the opportunity for side to side off-nagir viewing. The allows for more frequent coverage of a specific area, as well as for full-science stereoscopic imaging from two different satellite tracks (Lillesand and Kiefer 1994).

(1988a, 1988b, 1989). The spectral differences observed as a result of defoliation were wide spectral-band features, with the blue, red, near-infrared, and middle-infrared showing the greatest sensitivity for discrimination. Although current airborne and satellite sensors operate in these bands, there is a potential for optimizing sensor spectral bands (Leckie et al. 1988b). Examples of remote sensing studies dealing with forest damage assessment are presented in Table 7. From examination of these studies, it is evident that (i) the ability to remotely detect forest damage is related to the actual extent of damage; (ii) high spatial resolution data are generally required to quantify the changes that can be detected; and (iii) in general, visual assessment in combination with expert knowledge may be more successful than digital analysis of high-resolution data for monitoring change.

Ahern et al. (1991a) identified three areas of research required for spruce budworm damage assessment. These were (i) identification of optimal cost-effective spatial resolutions, (ii) radiometric corrections for large off-nadir viewing angles, and (iii) development of reliable methods for correcting for variable atmospheric path radiance and transmission. As these current limitations are overcome, operational aerial defoliation survey methods using multispectral scanner data should become feasible.

Biophysical Remote Sensing

In addition to identifying short-term change, remote sensing data can also be used to collect biophysical information that can be useful for monitoring and predicting long-term changes to ecosystems. In his review article on biophysical remote sensing, Jensen (1983) stated that data collected by remote sensing (ratio-scaled data) for biophysical variables may be more suitable for modeling and simulation than are land-use and land-cover information (nominal-scaled data), which are often used in modeling physical processes. Recent studies using remote sensing methods have focused on the study of biogeochemical processes, including biogeochemical cycles. For these studies, inventories of vegetation characteristics (e.g., biomass, primary productivity, photosynthetic activity) and physiologic processes (transpiration flux, leaf moisture content) are essential.

Characteristics of a plant canopy (e.g., composition, height, density, sociability) are, collectively, strong indicators as to the state of an ecosystem as a whole, and represent the physical interface for which optical remote sensing is able to provide quantitative measures. For example, changes in water and nutrient availability are reflected in the amount and seasonal duration of leaf area, in addition to changes in reflectance (NASA 1987). Conventional forest inventories acquired through the analysis of aerial photographs provide a starting point for predicting forest growth by characterizing forest stands with respect to species, age, stocking, and site quality. However, these standard forest inventories fail to describe stands adequately in terms of the key determinants to stand growth—the structure and quantity of the foliage present in the stand canopy.

Satellite data provide an attractive potential solution to this problem since these data are able to quantitatively characterize stand canopies via spectral reflectance at frequent intervals (Ahern et al. 1991b). In fact, the first five spectral bands of the Landsat TM sensor (Table 5) were designed to sense the biophysical properties of vegetation (Lillesand and Kiefer 1994). Some fundamental biophysical variables that can be measured directly include color and spectral signature, vegetation chlorophyll absorption characteristics, vegetation biomass, vegetation moisture content, soil moisture content, temperature, and texture/surface roughness (Jensen 1983). As an example, all other conditions being equal, a decrease in vegetation moisture content will be accompanied by an increase in reflectance in the middle-infrared spectral wavelengths. Hybrid variables can be derived from fundamental variables (e.g., vegetation stress can be derived from vegetation chlorophyll absorption characteristics and moisture content) (Jensen 1983). In addition to forest cover type, the most common forest characteristics that have been studied with remote sensing data involve stand structure; in particular, crown closure, basal area, leaf-area index (LAI), and tree size (Spanner et al. 1984a, Franklin et al. 1986, Peterson et al. 1986).

Jensen (1983) warns, however, that in order to extract meaningful information on biophysical properties the nature of spatial, spectral, temporal, and radiometric resolutions must be understood. These properties are loosely coupled with a number of factors that influence the optical properties of forest canopies. It is particularly important to understand the effects of these parameters on forest canopy spectral response in order to quantitatively interpret biophysical variables. These factors are summarized in Table 8. For example, correcting for atmospheric effects increases the slope of the regression line for TM spectral radiance and LAI, thereby producing greater sensor sensitivity to LAI (Spanner et al. 1984b, Running et al. 1986).

Estimates of ground biophysical variables from spectral reflectance measurements can be derived using two types of analysis techniques: (i) deterministic or stochastic canopy radiation models, or (ii) empirical spectral indices. Analytical techniques model the radiative transfer process between the land surface and the sensor to invert reflectance measurements to a particular physical parameter (Otterman et al. 1987, Goel 1988). Goel (1988) presents a useful overview of the factors affecting canopy reflectance (e.g., incoming solar flux, spectral properties of

Table 7. Examples of damage assessment of forests using remote sensing.

Condition	Synopsis	Reference
Insect damage	Used multitemporal Landsat MSS data and vegetation difference index to identify areas of forest canopy change.	Nelson 1983
Spruce budworm	Due to the date of SPOT simulation data acquisition (18 June 1983), spruce budworm damage assessment was limited; able to separate the previous years defoliation into two levels (severely defoliated and dead trees).	Buchheim et al. 1985
Spruce budworm	Evaluated the factors affecting defoliation assessment (radiometric, topographic, scene related, etc.) and emphasized that the magnitude of these factors can be larger than the range of differences between healthy and severely defoliated trees.	Leckie 1987
Spruce budworm	From *in situ* spectrometer measurements, determined that the most effective bands for discriminating different levels of defoliation were: 2030–2210, 660–670, 1560–1620, and 770–790 nm.	Leckie et al. 1988b
Mountain pine beetle*	Tested SPOT-enhanced visual products to determine effectiveness in detecting insect mortality; areas 1–2 ha in size with 80–100 percent red crowns could be detected; not suitable for control program.	Sirois and Ahern 1988
Eastern hemlock looper**	SPOT HRV multispectral data were classified to successfully discriminate two classes of eastern hemlock looper damage, moderate/severe and light.	Franklin 1989
Mountain pine beetle	MEIS 1.2-m data was superior to MEIS 3.4-m and conventional aerial photography for detection of red crowns through visual interpretation in British Columbia; natural color composites were optimal for visual assessment.	Kneppeck and Ahern 1989
Hail damage	Landsat TM imagery was used to assist in the mapping of a forested area damaged by hail and to assess damage in planning for an operational salvage harvest.	Gillis et al. 1990
Sugar maple*** decline	Found a close relationship between sugar maple decline and spectral (principal component 2) and texture (contrast) features in aerial multispectral video imagery; based on examination of single-tree canopies.	Yuan et al. 1991
Spruce budworm	7-m resolution MEIS data was acquired to classify cumulative defoliation and three levels of current defoliation (light, moderate, severe); a per-pixel MLC based on eight spectral bands achieved 72 percent accuracy for six classes relevant to defoliation survey; the majority of misclassifications were between adjacent healthy and current defoliation classes.	Ahern et al. 1991a
Norway spruce**** defoliation	Found that the decrease in TM band 4 reflectance was the single consistent spectral effect of moderate defoliation on Norway spruce (ratio methods seemed inappropriate when defoliation was the sole symptom of decline as opposed to defoliation and chlorosis).	Ekstrand 1994
Spruce budworm	SPOT multispectral data along with NDVI and chromaticity measures were used to discriminate four damage classes; discrimination of damage classes was improved when the sample sites were stratified by species composition, density, age, and height.	Franklin and Raske 1994

* *Dendroctonus ponderosae* [Hopk.]

** *Lambdina fiscellaria* [Guen.]

*** *Acer saccharum* Marsh.

**** *Picea abies* (L.) Karst.

Table 8. Factors affecting the spectral response of forest canopies.

Factors	Description	Reference
External		
Size of viewed area	Variability of the spectral response of a forest canopy will depend on the size of the instantaneous field of view.	Guyot et al. 1989
Sun elevation	Solar radiation penetrates more deeply into a canopy at steep angles; bidirectional reflectance increases in the visible and decreases in the near-infrared with increasing sun elevation, particularly with dense forest canopies; leaf transmittance is low in the visible, but up to 50 percent in the near-infrared.	Kimes et al. 1986, Guyot et al. 1989
Zenith view angle	Natural surfaces do not perform as Lambertian reflectors; spectral radiance of surfaces varies as a function of view, zenith, and orientation angles; bidirectional reflectance for continuous canopies is wavelength dependent.	Curran 1980, Stohr and West 1985, Guyot et al. 1989
Cloud cover	Clouds modify the irradiance level for a given sun elevation and significantly change the proportion of direct and diffuse radiation reaching the earth's surface.	Guyot et al. 1989
Atmospheric aerosols	Modify the optical path between the satellite and earth surface; wavelength dependent; more pronounced at shorter wavelengths.	Guyot et al. 1989
Wind speed	Affects the geometry of the forest canopy.	Guyot et al. 1989
Internal		
Orientation of tree rows (plantations)	Light penetration varies as a function of row direction (a function of plantation); these structural aspects of plantations are thought to be more directly correlated with spectral response than canopy cover.	Guyot et al. 1989, Danson and Curran 1993
Soil optical properties	Background spectra may confound changes in the spectral response of the overstory vegetation; optical properties of soil show an increase in reflectance from the visible to middle-infrared.	Ranson et al. 1986, Guyot et al. 1989
Canopy geometry (closure, density)	The most significant factor acting on the optical properties of forest canopies (controls the fractions of overstory and understory visible to the sensor).	Guyot et al. 1989
Terrain (slope angle and aspect)	Terrain elements account for appreciable variations in response in all wavelength bands; slope and aspect can produce a wide range of pixel values within one cover class; this effect is linked to solar elevation and azimuth.	Stohr and West 1985
Height, vigor, and comparison of species	Density, height, and vigor of vegetation and percent compositon of species affect the spectral response of forest canopies. These affects directly impact forest change assessment and classification.	Wickware and Howarth 1981, Riordan 1982, Price 1986

vegetation elements, canopy architecture, and scattering from the soil or ground-surface features) and how these factors can be used to model canopy reflectance. Nemani et al. (1993) describe radiation models as rigorous in their treatment of radiative transfer in vegetation canopies, but they are difficult to parameterize and are often developed for relatively homogeneous vegetation covers. Consequently, these are more suited to agricultural canopies than to heterogeneous forest canopies consisting of species mixtures with variations in leaf optical and structural properties. Radiative transfer models rarely simulate forest heterogeneity or generally require input data for parameterization at resolutions that are difficult to obtain. Research on invertible canopy models has made significant progress (e.g., Li and Strahler 1985, 1986; Goel and Grier 1986a, 1986b, 1988; Franklin and Strahler 1988) but, for forest conditions, such models are not yet operational (McGwire et al. 1993).

The majority of studies that estimate biophysical variables from remotely sensed data (Table 9) have used empirical techniques to relate spectral data and various derivatives to biophysical parameters. If biophysical parameters are strongly correlated with remotely sensed radiance data, then these data can be used to predict those biophysical characteristics for variable scene and sensor characteristics over large areas. For example, index-based techniques have been used to estimate vegetation parameters (e.g., LAI, PAR, biomass), or soil attributes (e.g., composition, brightness, moisture) (McGwire et al. 1993). If strong correlations could be obtained consistently with these biophysical parameters, they would prove useful for monitoring long-term environmental changes of such critical characteristics as primary productivity.

Curran (1980) observed that as biomass increases and the canopy becomes more complete (i.e., LAI increases), the relationship between multispectral reflectance and vegetation amount can be considered linear for the majority of cases. Numerous studies have since shown the correlation between remotely sensed red and near-infrared reflectance of coniferous forest stands to plant biomass (LAI) (Tucker et al. 1981; Spanner et al. 1984a; Badhwar et al. 1986a, 1986b; Franklin 1986; Running et al. 1986; Peterson et al. 1987; Spanner et al. 1990b). There is a consistent negative relationship between red radiance and LAI, and a weak or slightly positive relationship between near-infrared radiance and LAI. As a result of increased green vegetation and shadow within the canopy, there is a decrease in visible reflectance. An increase in near-infrared reflectance should also occur; however, increased shadow in a complex canopy acts to suppress such reflectance. This influence of canopy is significant, and even in stands with variable understory, canopy cover is considered the most important variable in determining canopy reflectance (Spanner et al. 1990a, Stenback and Congalton 1990). Conversely, in a coniferous forest plantation that is managed to maintain a large amount of green vegetation with little spatial variation, this relation may be weaker, as stand structural characteristics (tree density, mean tree height, mean tree diameter) become more closely correlated with stand spectral response (Herwitz et al. 1989, Danson and Curran 1993). For open canopies, near-infrared reflectance from understory, particularly broadleaved, species dominates the overall reflectance (Badhwar et al. 1986a).

Many of these investigations have suggested that simple transformations of band reflectances are more closely correlated with plant biophysical qualities (Wiegand et al. 1991), and are generally less sensitive to external variables such as the solar zenith angle. An example of one of these transformations is the "normalized difference vegetation index" (NDVI) (Badhwar et al. 1986b), although there are also various derivatives of NDVI (White 1991, Kogan 1990). Along with NDVI, the most common vegetation indices utilize the information content of the red and near-infrared canopy reflectance or radiances. This transformation is highly correlated with green-leaf biomass (Jensen 1983). Chlorophyll absorption in the visible portion (0.5–0.7 µm) of the spectrum is high (reflectance <20 percent), whereas reflectance and transmittance are about equal in the near-infrared portion (40–50 percent) (Smith 1983). This physiological relationship has been used to estimate the intercepted photosynthetically active radiation (IPAR) of plant canopies (Asrar et al. 1984, Sellers 1985, Baret and Guyot 1991, Sellers et al. 1992), percent canopy cover (Richardson and Wiegand 1977), chlorophyll content (Tucker 1977), and LAI (Asrar et al. 1984, Baret and Guyot 1991) through the use of various ratios (Sellers 1985). Nemani et al. (1993) used the middle-infrared band of Landsat TM to correct for understory and background effects on NDVI for estimating LAI. Some of these ratios and their applications are described in Table 10. It must be remembered that these indices are also sensitive to the internal and external factors that affect spectral reflectance of vegetation (i.e., those described in Table 8). However, Goward et al. (1994) found that variations in vegetation indices for western Oregon originate from changes in both canopy spectral characteristics and background spectral reflectance, rather than from simple variations in LAI or percent canopy closure. Caution must therefore be taken when relating changes in vegetation indices to vegetation physiognomic properties at regional and global scales.

The use of vegetation indices with wide spectral band remote sensing data is not appropriate for areas of low green canopy cover since background rock, soil, ground surface, and litter materials produce a range of vegetation index values (Elvidge and Lyon 1985, Huete et al. 1985, Huete and Tucker 1991). The development of high spectral resolution imaging sensors (e.g., AVIRIS, CASI) has led to the study of terrestrial materials using new analysis techniques. Once the physical nature of the materials within the sensor field of view are determined, quantitative

Table 9. Examples of biophysical remote sensing of forests.

Variable(s)	Synopsis	Reference
Structural classes (crown closure, size class)	Feature selection identified TM simulated bands 4, 7, 5, and 3 as optimal for forest structural analysis; moderately successful for identifying four crown-closure classes and two size classes.	Spanner et al. 1984a
LAI	Various ratios of red and near-IR were correlated with LAI.	Running et al. 1986
LAI	Strong correlations between LAI and Landsat TM reflectance of aspen (*Populus* spp.) early in the growing season disappeared as the understory developed.	Badhwar et al. 1986a
Canopy closure/ basal area	Canopy closure was most closely related to spectral response of TMS bands and ratios; basal area showed strong correlations with some species, e.g., red fir (*Abies magnifica* A. Murr.) and lodgepole pine (*Pinus contorta* Dougl.), but not white fir (*Abies concolor* [Gord. & Glend.] Lindl).	Peterson et al. 1986
LAI	A strong positive relationship was detected for the IR/red reflectance ratio; explained by a strong asymptotic inverse relationship between LAI and red reflectance and a flat response between LAI and IR reflectance.	Peterson et al. 1987
Spectral shift *(blue shift)*	Detected a 5-nm shift away from the normal inflection point of the red edge reflectance feature towards shorter wavelengths; a result of stress.	Rock et al. 1988
Forest damage (foliar loss [percent])	TM shortwave-IR to near-IR band ratios were found to correlate well with ground-based measurements of forest defoliation.	Vogelmann and Rock 1988
Forest productivity	TM data, in conjunction with biogeographical and ground plot data, were used to successfully model forest productivity at the landscape level, but the reliability of single pixel estimates was poor.	Cook et al. 1989
LAI	The relationship between LAI of coniferous forests and TM data corrected for atmospheric effects and sun–surface–sensor geometry was affected by canopy closure, understory vegetation, and background reflectance.	Spanner et al. 1990a
Timber volume	Vegetation-condition indices generated from shortwave-IR and near-IR TM bands showed strong correlations with net annual spruce–fir volume change; useful for stand development forecasting.	Ahern et al. 1991b
Timber volume	A strong relationship (-0.79) was observed between the volume of coniferous forest compartments and spectral radiance recorded by Landsat TM, particularly TM band 5 (estimates for compartments with small volumes were better than for those with large volumes).	Ardö 1992
Timber volume	Found good correlations between stand volume and normalized difference of TM bands 4 and 5 for homogeneous stands (however, this capability was reduced at low volumes due to spatial inhomogeneities and at high volumes due to complete canopy closure).	Gemmel and Goodenough 1992
Single-tree defoliation	A linear relationship existed between visually estimated tree defoliation for trees with >20 percent defoliation and spectral features of 40-cm MEIS data; NDVI provided the best correlations with defoliation.	Leckie et al. 1992
LAI	Demonstrated the potential use of Landsat TM data for studying seasonal dynamics in forest canopies by obtaining strong correlations between LAI and NDVI for September 1988 and March 1989.	Curran et al. 1992

Table 10. Examples of ratio-based indices for biophysical studies.

Index	Landsat TM equivalent	Description	Origin
Near-IR / red reflectance ratio	TM4/TM3	Responds to changes in amount of green biomass, chlorophyll content, and leaf-water stress.	Birth and McVey 1968, Tucker 1979
Normalized Difference Vegetation Index (NDVI)	(TM4-TM3)/(TM4+TM3)	Responds to changes in amount of green biomass, chlorophyll content, and leaf-water stress.	Rouse et al. 1974, Tucker 1979
Infrared index	(TM4-TM5)/(TM4+TM5)	Infrared index more closely tracks changes in plant biomass and water stress than NDVI.	Hardisky et al. 1983
Moisture stress index	TM5/TM4	Tracks changes in plant water stress.	Rock et al. 1985
Leaf water content index	-log[1-(TM4-TM5)] -log[1-(TM4ft-TM5ft)] ft represents reflectance in the specified bands when leaves are at their max. relative water content	Responds to changes in water stress.	Hunt et al. 1987
Mid-IR index	TM5/TM7	Shows a strong correlation with soil moisture.	Musick and Pelletier 1988
Vegetation Condition Index (VCI)	100(NDVIij-NDVIminj) NDVImaxj-NDVIminj	Portrays weather dynamics more effectively than NDVI for nonhomogeneous areas by removing the influences of geographic resources such as climate, soil, vegetation type, and topography.	Kogan 1990
Perpendicular Vegetation Index (PVI)		Attempts to eliminate differences in soil background and is most effective under conditions of low LAI (arid and semi-arid environments).	Richardson and Wiegand 1977
Soil Adjusted Vegetation Index (SAVI)	(TM4 + L1)/(TM3 + L2)	Incorporates parameters (L1, L2) to minimize soil-brightness induced variations.	Huete 1988
Transformed Soil Adjusted Vegetation Index (TSAVI)		Modifications of Huete (1988) SAVI to compensate for soil variability due to changes in solar elevation, leaf-angle distribution, and LAI.	Major et al. 1990, Richardson and Wiegand 1990
Greenness Vegetation Index (GVI)	Gram-Schmidt orthogonalization	Greenness vegetation index is a measure of the amount of vegetation present relative to bare soil.	Kauth and Thomas 1976
Mean Greenness Vegetation Index (MGVI)	Principal components analysis	Principal components are used to identify the extent of soil and vegetation in the scene.	Misra and Wheeler 1977

(*Adapted from* Cohen 1991, Major et al. 1990.)

estimates of their abundance can be made using spectral mixture analysis methods (Roberts et al. 1993, Foody and Cox 1994). For example, spectral mixing methods have been used to model the relative contributions of green vegetation and soils to image spectra (Huete 1986; Smith et al. 1990a, 1990b; Gong et al. 1992b; Roberts et al. 1993). Such methods provide derived quantitative estimates of vegetation and soil abundance (e.g., Smith et al. 1990a, 1990b), as well as nonphotosynthetic vegetation and shade (Roberts et al. 1993).

Leaf area of closed canopy forests is an important ecological parameter used in numerous studies. Leaf-area index (LAI) is a standard expression for the leaf area of a plant community and is defined as the total leaf area per unit ground cover (Herwitz et al. 1989). Light interception, gas exchange, photosynthesis, and biomass production are all closely related to LAI (Peterson et al. 1987, Herwitz et al. 1989, Bonan 1993, Nemani et al. 1993). Regional variations in LAI have been found to be linearly related to site water balance (Nemani and Running 1989) and aboveground net primary production and stand volume (Gholz 1982, McLeod and Running 1988). For global change studies, satellite-derived measures of vegetation cover type and LAI may be used to provide more accurate estimates of the carbon content and exchange rates of global vegetation than are possible with current data (Running et al. 1986). For instance, Mack et al. (1990) used vegetation indices derived from Landsat MSS data to examine the relationship between vegetation cover and CO_2 flux density for agricultural and forested areas.

From the above discussion, it is evident that remote sensing has the potential to provide information for the definition and mapping of spatial patterns in ecosystems, as well as for their change in time. This includes not only the monitoring of biophysical variables related to forest ecosystem structure and processes, but also the definition of forest ecosystem units as presented in the following discussion.

Forest Classification

Landsat MSS data have become widely used in a variety of land resource applications, including forestry. Forestry applications initially focused on the enhancement of Landsat MSS data for visual interpretation, but as digital image analysis techniques became available, visual analysis was gradually replaced by more automated techniques for extraction of forest information.

Landsat MSS has been used primarily for generalized forest-type mapping (Bryant et al. 1980, Kalensky et al. 1981, Pettinger 1982). Success has also been achieved for forest site-type mapping (Tom and Miller 1980, Hame 1984) and for species and structural mapping, but only in association with the careful treatment of training statistics (Walsh 1980) or the addition of ancillary variables (Strahler et al. 1980) (Table 11). Classifications have been improved by integrating MSS spectral data with digital elevation data and associated geomorphometric variables (Strahler et al. 1980, Franklin et al. 1986, Franklin 1987), as well as with texture measures (Franklin and Peddle 1989) (Table 11).

Landsat MSS has proven successful for generalized forest mapping due primarily to the large spatial resolution (80 m) that averages the spectral characteristics of forest structure, thereby reducing variance and spectral overlap between broad cover classes. This produces spectral characteristics for general cover types that often fit the normal distribution of parametric classifiers, particularly for areas of low relief. The addition of ancillary data (e.g., geomorphometric variables) or additional feature processing (e.g., texture) provides enhanced classification results.

In Canada, the use of remote sensing has been integrated into Ecological Land Survey approaches in the form of multistage sampling procedures for various scales of survey (Rubec 1983) (Table 12). Landsat MSS has been used in many ecological surveys, providing information at the ecoregion and ecodistrict levels (Wickware and Rubec 1989). The combined use of Landsat transparencies, in a multistage approach with other remote sensing data, has proven useful in the prefield, field, and postfield activities involved in the Ecological Land Survey of numerous areas in northern Canada (Rubec 1983). Digital image analysis techniques using Landsat MSS did not provide suitable results for mapping ecological land classes at detailed levels (initially reported by Thie [1976]).

Improved spatial, spectral, and radiometric characteristics of Landsat TM have led to numerous forest studies for the purpose of classifying forest types and structural characteristics. Congalton et al. (1993) stated that the spatial resolution of SPOT and Landsat TM are a major improvement over Landsat MSS. A survey of the literature indicates that more detailed information is available from Landsat TM data (Table 13). However, due to the increased heterogeneity of the spectral data representing cover classes, the extraction of information requires more sophisticated analysis and classification techniques. The increase in spectral "noise" that accompanies higher spatial resolution data indicates that such noise is usually related to variations in structural properties of forest communities (Peterson et al. 1986). Hence, TM may provide researchers with a greater ability to extract stand structural characteristics.

SPOT data have now come into wide use for land-cover and land-use mapping. For forest mapping, concern has recently been raised regarding the low dynamic range of

Table 11. Forest classification with Landsat MSS.

Variable(s)	Technique*	Description	Reference
Spatially complex vegetation	UC (MLC)	Difficult correlating spectral classes and ground classes; small land-cover units and rugged terrain complicated interpretation; UC not demonstrated to be superior to SC.	Townshend and Justice 1980
Coniferous species (including stand and site characteristics) (MLC)	controlled clustering	Twelve surface-cover types (merged from 59 spectral clusters) were mapped to an average accuracy of 88.8 percent; slope angle, aspect, and surface cover affected spectral variability.	Walsh 1980
Timber height and density (to estimate timber volume for homogeneous strata)	(i) UC; (ii) model 'region type' with DTM	The authors developed a stratification procedure for a high relief forest environment incorporating tone (MSS), texture, and geomorphometric variables.	Strahler et al. 1980, Franklin et al. 1986
Forest Site Index (9)	LDA spectral and ancillary variables	Achieved 97 percent training accuracy when combining 19 image and map variables; MSS alone achieved 43 percent.	Tom and Miller 1980
Conifer species Canopy density Crown diameter	UC (guided clustering)	Guided clustering defined a maximum number of low variance spectral classes; by matching spectral curves of known and unknown spectral classes it was possible to assign spectral classes to categories.	Mayer and Fox 1981
Softwood, hardwood regeneration	SC, UC (MLC)	Performed generalized forest-type mapping (reconnaissance stage) and emphasized a multi-stage approach.	Kalensky et al. 1981
Anderson's classification (Levels I, II, III)	modified clustering (MLC)	Successful for mapping at Anderson's Level I (83.0 percent); detailed mapping at Levels II and III achieved 52.2 percent accuracy.	Pettinger 1982
Forest site types	MLC	Used a multi-stage process to improve the efficiency of mapping site types.	Hame 1984
Forest cover types (species level for conifers)	SC, UC (MLC)	Results indicated that classification accuracy is more dependent on forest composition and distribution than on a particular classification scheme.	Hudson 1987
Mountainous landscape classes	LDA	Geomorphometric and MSS data (75 percent); MSS data alone (46 percent).	Franklin 1987
Forest types (within a moderate relief boreal environment)	LDA	Texture algorithm improved classification; geomorphometric variables provided the greatest improvement to classification.	Franklin and Peddle 1989

* SC = supervised classification; UC = unsupervised classification; MLC = maximum likelihood classification; LDA = linear discriminant analysis.

Table 12. Relationship between remote sensing systems and ecological land survey mapping scales and levels.

Remote sensing source	Ecological land survey mapping level	Mapping scales
Satellite imagery	Ecoregion	1:3 000 000 – 1:1 000 000
High altitude photography	Ecodistrict	1:500 000 – 1:125 000
Moderately high altitude photography	Ecosection	1:250 000 – 1:50 000
Low altitude photography	Ecosite	1:50 000 – 1:10 000
Low altitude or ground photography	Ecoelement	1:10 000 – 1:2 500

(*From* Wickware and Rubec 1989.)

data acquired over forested regions. This may prevent satisfactory classification results (Borry et al. 1990, De Wulf et al. 1990). It has also been noted that there is high correlation between SPOT XS Bands 1 and 2. De Wulf et al. (1990) had limited success extracting forest-stand parameters (e.g., stand density, stand age, average tree diameter, stand basal area, average canopy height, and stand volume) from both multispectral and panchromatic data and as a result considered SPOT data as L-resolution[6] (Strahler et al. 1986) with respect to forest canopy structure. For visual and digital analysis of SPOT multispectral data, the date of acquisition is a key element to successful forest mapping and analysis; data acquired in the early part of the growing season provide superior results (Borry et al. 1990). Upon achieving unimpressive classification accuracies for vegetation classes using SPOT data (corrected for terrain), Baker et al. (1991) noted that spectral classification alone may not be sufficient. The inclusion of certain geomorphometric variables (Franklin and Wilson 1991, Franklin et al. 1994) in a high-relief environment, as well as texture features (Franklin and Peddle 1990), generally improved the classification accuracies achieved with SPOT multispectral data.

Information content in an image is expressed by the 'intensity' of each pixel (i.e., tone or color) and by the spatial arrangement of pixels (i.e., texture, shape, and context) in the image (Lee and Philpot 1991). Campbell (1987) defines image texture as the apparent roughness or smoothness of an image region, usually the result of an irregular surface being illuminated from an oblique angle and causing a pattern of highlighted and shadowed areas. Texture is an important functional attribute of a remotely sensed image and is therefore a significant contributor to scene information extraction. Although texture has long been recognized as an important clue in the visual recognition of objects in aerial photographs, conventional automated processing traditionally has not exploited this component of remote sensing data.

It is well known that actual landscapes consist of a spectrally diverse assemblage of features, which become increasingly complex as spatial resolution increases. Indeed, the use of texture explicitly implies that the resolution cells are smaller than the elements in the scene model, because numerous measurements are required for each element or class in order to allow the characteristic spatial texture to occur (Woodcock and Strahler 1987). To extract more information from digital remote sensing data, image classification should include information regarding the overall pattern of variation that characterizes each category. However, the majority of image classification procedures, particularly in operational use, rely on spectral 'intensity' characteristics alone, and thus are oblivious to the spatial information content of the image. These types of per-point classifiers do not perform well in environments where there is an excess of boundary pixels or where there is substantial spectral overlap between the chosen informational classes (Martin et al. 1988).

Textural algorithms, on the other hand, attempt to measure image texture by quantifying the distinctive spatial and spectral relationships that occur among neighboring pixels. For a forested environment, where local variance is high, texture measures should be more valid than contextual methods because they rely on spatial variation to differentiate classes (Woodcock and Strahler 1987). In response to the need to extract information based upon the spatial arrangement of digital image data, numerous texture algorithms have been developed. These include methodologies based upon: (i) structural approaches (Conners and Harlow 1980); (ii) spatial-frequency patterns (Bajcsy and Liebermann 1976); (iii) first-order statistics (Hsu 1978, Irons and Petersen 1981, Arai 1993);

[6] L-resolution, a term defined by Strahler et al. (1986), indicates that the spatial resolution cells within the remote sensing image are larger than the elements within the ground scene. These elements on the ground are therefore not resolvable. H-resolution, on the other hand, indicates that the spatial resolution cells are smaller than the elements within the scene; therefore the individual elements may be resolved.

Table 13. Forest classification with Landsat TM.

Variable(s)	Technique*	Description	Reference
Alpine and subalpine communities, Montane forests	TM band ratios, NDVI, LDA	TM transformations combined with landscape variables were able to discriminate alpine and subalpine vegetation types; forest types in the Montane zone were not distinguishable.	Frank 1988
Nine forest classes (species, terrain derived)	SC, MLC	TM provided superior forest-type mapping and condition assessment information than MSS; average accuracy for nine forest classes was 69 percent; improved when forest categories were merged.	Hopkins et al. 1988
Nine natural resource categories	SC, MLC	Tested a variety of TM band combinations and found that six TM bands provided the highest overall classification accuracy (92.4 percent).	Karteris 1990
Species and age groups (pine plantations)		TM imagery was inadequate for separating species; age classes were separable.	Coleman et al. 1990
Landscape classes, high relief	LDA	Classification accuracy increased from 55.8 percent to 77.6 percent when geomorphometric variables were included with TM data.	Franklin and Moulton 1990
Canopy closure and forest understory	UC	The data were stratified into three categories of canopy closure; presence or absence of understory in each category was then evaluated using spectral response pattern analysis; understory presence or absence (55–69 percent accurate).	Stenback and Congalton 1990
Three forest types and eight land-cover classes	PCA, LDA, MLC	TM data were transformed using PCA and combined with geomorphometric variables to provide mapping accuracies of 76 percent.	Franklin 1992
Successional stages	UC, MLC	A wetness index and a TM 4/5 ratio and TM 4 were the best features for distinguishing between old-growth and mature forests; accuracy (71.7 percent).	Fiorella and Ripple 1993
Species, size class (structure, crown closure)	SC, UC ancillary variables	In-depth spectral analysis was performed to determine the strength of the correlation between the spectral data and vegetation; SC and UC were performed and similarities between the spectral statistics for each classification were compared using a clustering algorithm (accuracies > 80 percent).	Congalton et al. 1993
Six forest and five nonforest classes (canopy change)	Vegetation indices "guided" clustering	"Guided" clustering of Landsat TM bands and various vegetation indices provided classification accuracies of 75 percent for six forest classes and five nonforest classes; misclassification resulted from stands being a mix of two or more species that also differ in size, density, crown closure, and age.	Bauer et al. 1994

* SC = supervised classification; UC = unsupervised classification; MLC = maximum likelihood classification; LDA = linear discriminant analysis; PCA = principal component analysis.

(iv) second-order statistics (Haralick et al. 1973, Galloway 1975, Sun and Wee 1982); (v) texture spectrum (Wang and He 1990, Gong et al. 1992b); and (vi) spectral texture pattern matching (Lee and Philpot 1991). Useful summaries of methodological approaches to measuring texture are provided by Haralick (1979) and Marceau (1989).

In studies comparing various texture measures, second-order statistical techniques are generally identified as superior to other methods (Weszka et al. 1976). In particular, the grey-level cooccurrence matrix (GLCM) technique has proven to be optimal for capturing the textural content of an image (Conners and Harlow 1980, Gong et al. 1992a, Treitz et al. 1993). Statistical approaches, such as those developed by Haralick et al. (1973) and Sun and Wee (1982), make use of grey-level probability density functions that are generally computed as the conditional joint probability of pairs of pixel grey levels in a local area of the image.

A number of studies incorporating texture analysis into classification of land cover and land use are outlined in Table 14. It is evident that texture data provide additional information that can be used for the classification of certain forest structural attributes. For instance, stand structural characteristics (e.g., diameter at breast height [DBH], crown diameter, density, basal area, age) have been found to be highly correlated with texture images generated from SPOT panchromatic data (Cohen and Spies 1992). Texture also appears to be more evident at higher spatial resolutions (e.g., 10 m) because at these levels stand structural characteristics tend to dominate the scene (Yuan et al. 1991, Franklin and McDermid 1993).

Research into the classification of remotely sensed data has been pursued for approximately three decades and has involved many different strategies (e.g., supervised/unsupervised, per-pixel/per-field, textural, contextual). Pixels are grouped into various classes using a suitable classifier (e.g., minimum distance, maximum likelihood) or multivariate analysis (e.g., discriminant, principal components) or both. No single strategy has proven best for all situations; the most suitable approach is dependent upon the nature of the data collected, the availability of additional or collaborative terrain data, the characteristics of the surface being "sensed", and the ultimate objectives and/or products desired from the classifier. The analyst is responsible for devising suitable strategies for collecting remote sensing and ground information, and for applying suitable analysis techniques to the data for a particular environment. To analyse the data correctly, the analyst requires a good understanding of the physical nature of the remote sensing data, as well as the statistical tools used to group such data into relevant classes.

The analyst frequently does not have a large choice of classification algorithms in which pixels or comparable spatial neighborhoods are assigned to a particular class. Traditionally, classification algorithms have relied on spectral data alone for pixel assignment. As discussed by Robinove (1981), the philosophical basis for multispectral classification implies that the multispectral data represent an acceptable surrogate for the attributes of the ground features that are of interest and that spectral classes separated within the data correspond to a distribution of ground-cover classes. In fact, information classes are generally subsets of a continuum of reflectances and in classification are applied against the geometric character of the classifier (Richards and Kelly 1984).

Given the relatively small range of classification algorithms available, analysts may be forced to select classifiers that may not be appropriate for the data they are analyzing. This situation is becoming more problematic, particularly as new data types with increased spatial, spectral, and radiometric resolutions become available. Some of the classifiers commonly used are statistical in nature and include nonparametric classifiers such as minimum-distance-to-means, parallelepiped, and linear discriminant analysis (LDA) (Duda and Hart 1973, Tom and Miller 1984, Campbell 1987, Kershaw 1987). Parametric classifiers are also used, such as the maximum-likelihood classifier (MLC) and its sophisticated extension, the Bayesian classifier (Campbell 1987).

Parametric classifiers, such as the MLC, have become widely used in operational remote sensing. These classifiers calculate the statistical probability of each pixel value belonging to each class or category, as defined by the analyst; they are then assigned to the class with the highest probability. This sequence of events is performed by first taking into account the mean vector and covariance matrix of the spectral categories and then calculating probability density functions (PDF). However, the MLC model assumes normality, whereby the pixels sampled to define the decision rules of the classifier possess a normal or Gaussian distribution. This assumption has been reasonable for common spectral response patterns, which are encountered when using medium to low spatial resolution data (e.g., Landsat MSS - 80 m) (Lillesand and Kiefer 1994). The Bayesian classifier is similar to the MLC, but allows for the input of *a priori* probabilities for each class. These are then multiplied by the PDF determined from training data so as to quantify the posterior probability (Campbell 1987). The use of *a priori* probabilities in MLC has been shown to improve classification accuracies (Strahler 1980), but the approach is often not implemented since appropriate information is rarely known.

Table 14. Some applications of texture analysis for land-cover classification.

Texture method(s)	Synopsis	Reference
Grey-Level Cooccurrence Matrix (GLCM)	Demonstrated improved classification accuracy through the integration of texture features with 20-m airborne MSS data; improvement was more pronounced with a detailed classification scheme separating damaged and undamaged forest species.	Teillet et al. 1981
GLCM	Incorporating texture features into a linear discriminant analysis of Landsat MSS data improved accuracies up to 7.1 percent; using four orientations of the cooccurrence provided higher accuracies than using average textures; this could be related to topographic orientation (e.g., slope/aspect).	Franklin and Peddle 1989
GLCM	Classes containing either mixed vegetation patterns or possessing a strong relationship to structural features (e.g., topography) showed improved classification accuracy using tone and texture information.	Franklin and Peddle 1989
GLCM	The authors found significant improvement in classification accuracy for some land-cover classes when incorporating texture measures; window size is a dominant factor affecting accuracies.	Marceau et al. 1990
First-order statistics: Standard deviation	Texture processing was compared to per-field sampling and low-pass filtering to improve land-cover classification accuracy; texture improved accuracy 2.4 percent for single-date and 3.9 percent for a two-date analysis.	Curran and Pedley 1990
GLCM	Texture measures for TM data were greater than for MSS data; by adding texture features to a multitemporal data set, classification improved 1.6 percent to 4.7 percent.	Arai 1991
GLCM	When texture features were incorporated into classifications of land cover in a moderate/high relief environment using synthetic aperture radar and SPOT multispectral data, accuracies increased 11 percent and 15 percent, respectively.	Peddle and Franklin 1991
First-order statistics: Standard deviation Absolute difference	Texture of the SPOT 10-m data was strongly correlated with stand structural characteristics, whereas TM texture was weakly correlated; the spatial resolution of TM data is too coarse to detect the spatial variability within the forest stands studied.	Cohen and Spies 1992
First-order statistics: Variance	The range of variability derived from image semivariograms, calculated over lodgepole pine stands, were used to identify optimal window sizes and were most useful for estimating canopy coverage.	Franklin and McDermid 1993

When using the MLC, certain preprocessing procedures can be applied to the data to render them more amenable to the statistical assumptions of the classifier. These procedures are intended to reduce variance within the spectral classes, which can be considered either as noise or inherent heterogeneities within the land-cover class. These procedures include multivariate transformations of feature space, such as principal components analysis (PCA), which is used to examine the interrelationships between a large number of spectral vectors. PCA is also used to reduce the dimensionality of the original data with minimal information loss.

Spatial filtering[7] has been used as a preprocessing and/or postprocessing technique to improve classification accuracy (Cushnie and Atkinson 1985, Toll 1985). These context-dependent operators come in a variety of forms (e.g., mean, median) and are used to alter a pixel value according to its relationship with pixel values within a specified neighborhood or window. For example, a mean filter will smooth an image to greater degrees as the window size or array of pixels upon which the filter is applied is made progressively larger. A median filter, on the other hand, will smooth noise and also retain edges or boundaries. Both approaches effectively reduce the spatial resolution of the data and, logically, one must question the degree of information lost in such a process. Similar techniques can be applied after the data have been classified. To improve the accuracy of per-point classifications, a postclassification smoothing filter can be applied to the classified data, whereby an isolated class (noise) is assigned to the class category representative of the majority of pixels surrounding it (Thomas 1980). This technique, however, does not incorporate the true spatial characteristics of the class; it is only concerned with context as it relates to classified data and will only be effective for isolated pixels or groups of pixels (Lee and Philpot 1991).

Improvements in per-pixel classification have been observed with the use of linear discriminant analysis (LDA) (Tom and Miller 1984). This method relaxes the restriction of the data meeting a specified distribution (i.e., normal) and results in decisions for assigning pixels to a particular class that are more flexible, although perhaps less certain. As a result, the data play a much more prominent role in the creation of decision rules. LDA uses the pooled covariance matrix and reduces a multivariate problem to a univariate one by defining the weighted combination of input variables that best describe the separation among the groups (Tom and Miller 1984, Franklin 1992). As a result, LDA is less sensitive to the number of input variables than is MLC (Peddle 1993).

Efforts are currently being placed on the use of contextual classifiers to extract spatial information (Wharton 1982, Gurney and Townshend 1983, Gong and Howarth 1992, Gong 1994). Whereas texture refers to the spatial variation within a contiguous group of pixels that contribute to the overall appearance of the image, context refers to the spatial relationships of a pixel (or group of pixels) to pixels in the remainder of the image (Gurney and Townshend 1983, Campbell 1987). The basis of contextual classification lies with the premise that pixels of a given class are likely to be surrounded by pixels of the same class. This premise is likely to hold true for classes that are larger than the pixel size. However, at high spatial resolutions individual spectral components of land-cover classes become distinguishable. This spatial/spectral variability may compromise contextual classification in certain environments. Treitz et al. (1992) used SPOT data and a contextual classifier to improve land-use classification accuracy in a rural–urban fringe environment, which contained numerous land-use classes (discrete variables). In a forest and certain other environments, continuous variables may dominate and, under such circumstances, the premise for contextual classification may not be valid.

New developments in image classification include nonparametric classifiers (Skidmore and Turner 1988); advanced iterative clustering techniques (Guo and Haigh 1994); the use of fuzzy sets for information representation (Wang 1990a, 1990b; Foody and Cox 1994); evidential approaches for multisource data analysis (Lee et al. 1987, Wilkinson and Megier 1990, Veronese and Mather 1992, Peddle 1993); and neural networks (Benediktsson et al. 1990, Ersoy and Hong 1990, Bischof et al. 1992, Fernandez 1992, Foody et al. 1992, Benediktsson et al. 1993). Evidential and neural-network classifiers have a number of advantages when compared to many statistical classifiers: (i) they are not restricted by underlying statistical models (e.g., normal distribution); (ii) they are not sensitive to variance thresholds; (iii) they are able to adequately handle increased numbers of input variables; and (iv) they are capable of processing data of different variable types (e.g., nominal, ordinal, interval, and ratio) (Benediktsson et al. 1993, Peddle 1993).

Neural-network and evidential-reasoning classifiers have demonstrated superior classification capabilities when compared to traditional statistical classifiers (e.g., LDA, MLC) (e.g., Downey et al. 1992, Foody et al. 1992, Peddle 1993), particularly for nonnormally distributed training data (Benediktsson et al., 1993). The neural-network classifier performs a segmentation of the original data to different spatial resolutions (scales). Spectral signatures and spatial frequency textural information are used to guide an anisotropic diffusion process that smooths within-cover-class segments at different scales (Fernandez 1992). Although these classifiers show promising classification results, they are generally slower to train than traditional statistical classifiers. For most neural-network classifiers,

[7] Spatial filtering is a localized enhancement process by which pixel values from an original image are modified on the basis of the grey levels of neighboring pixels. Spatial filtering is performed on image data to emphasize or deemphasize image data of certain spatial frequencies (i.e., the roughness of the tonal variations occurring in an image). Low-pass filters are used to emphasize low-frequency features (e.g., agricultural crops) whereas high-pass filters are used to emphasize high-frequency features (e.g., road networks, geologic lineaments).

the training process is computationally very complex and requires a large number of training samples; such requirements may translate into a long implementation phase.

Franklin and Wilson (1992) used a three-stage approach to classification; it was initiated with a quadtree-based segmentation operator, followed by a Gaussian minimum-distance-to-means test, and then a test incorporating ancillary geomorphometric data and a spectral curve measure. Knowledge-based and expert systems promise to improve remote sensing image classification through the integration of knowledge and reasoning (Schowengerdt and Wang 1989, Srinivasan and Richards 1990, Ton et al. 1991). However, these attributes are often site and application specific (Wang and Newkirk 1988, Skidmore 1989), a situation that renders difficult the widespread use of such techniques.

Summary

The current role of remote sensing for forestry and ecological land classification has been described earlier in this report. An examination of the relevant literature has revealed that the results of digital image classification for forestry studies using remote sensing data are, at best, varied. This can be largely attributed to an incorrect matching of remote sensing data to the variables (information classes) being sought and/or use of inappropriate classification algorithms for the distribution of the data. However, when suitable information requirements are applied to the appropriate remote sensing data set, along with the appropriate analysis techniques, results can be positive (Pettinger 1982, Hame 1984, Franklin 1987, Franklin and Peddle 1989, Congalton et al. 1993). In such studies, the value of satellite data for forest classification has been clearly demonstrated.

In response to concerns regarding environmental change as a function of changing climatic conditions, substantial remote sensing research is being directed toward the biophysical modeling of forest-stand parameters. Some success has been observed in the form of strong correlations between forest-stand parameters (e.g., leaf-area index) and spectral reflectance or spectral indices (Curran et al. 1992). These relationships may prove useful for monitoring subtle changes in primary productivity and other ecological processes as ecosystems respond to changing climatic conditions.

Airborne sensors that generate high spatial and spectral resolution data are now available for remote sensing applications. The data generated from these sensors are not suited to traditional image analysis techniques developed for use with Landsat MSS data. Research is currently underway on image analysis techniques that attempt to incorporate textural and contextual information into decision rules. Also, classifiers that are not limited by data-distribution rules (i.e., Gaussian) are being developed to operate with a variety of data types, including nominal data sets. Such classifiers should prove useful for the analysis of high spatial resolution remote sensing data in conjunction with other types of spatial data.

THE FACTOR OF SPATIAL RESOLUTION (SCALE) IN REMOTE SENSING FOR FORESTRY

Spatial resolution is a fundamental concept in remote sensing and plays a significant role in the planning of any remote sensing investigation. Townshend (1981) and Forshaw et al. (1983) provide insightful backgrounds on the concept of spatial resolution and its various meanings. Here, we consider spatial resolution as the instantaneous field of view (IFOV) of the sensing system, which is the area on the ground viewed at any particular instant in time. With this definition, spatial resolution is analogous to the scale of the observations (Woodcock and Strahler 1987). For the purpose of this discussion, the term spatial resolution will be used not only in the traditional sense, but also as a surrogate for scale (Csillag 1991, Lam and Quattrachi 1992).

Spatial Resolution (Scale) and Multispectral Classification

One of the major considerations in any remote sensing forestry application is to determine the spatial resolution of the data that best meets the objectives of the project. Thus, it is important to understand how spatial resolution affects the spectral and spatial expression of forest attributes. For example, increased spatial detail may not necessarily improve classification performance (Markham and Townshend 1981, Buis et al. 1983). Such conditions have been observed for forest environments as spatial resolution becomes finer than 60–80m (Sadowski et al. 1977, Latty and Hoffer 1981, Nelson et al. 1984). Researchers investigating the effects of spatial resolution on classification accuracy have generally found that classification performance improves at lower spatial resolutions for various classification hierarchies (Latty and Hoffer 1981, Markham and Townshend 1981, Brass et al. 1983, Townshend 1983, Irons et al. 1985, Cushnie 1987). Wiersma and Landgrebe (1979) identified two counteracting forces that affect classification accuracy as a function of spatial resolution. These are: (i) heterogeneous targets and (ii) the percentage of boundary pixels within a scene. As spatial resolution increases, the proportion of pixels falling on, or near, boundaries of objects in the scene decreases, thereby reducing the number of mixed pixels and hence improving classification accuracy. However, higher spatial resolution also increases the spectral variance for cover types which, in turn, adversely affects the spectral separability of classes. Changes in classification accuracy that accompany changes in spatial resolution are thus a function of the relative importance of 'scene noise' and boundary pixels (Markham and Townshend 1981). It is also notable that scene noise may vary considerably among land-cover categories and across spectral bands for the same cover class.

Closely associated with the high spectral variability of high-resolution imagery is the large amount of spatial information inherent in the data. Over the past 10 years, as higher spatial resolution satellite and airborne remote sensing data became available, it was discovered that conventional analysis techniques did not provide satisfactory results (Townshend 1983, Hodgson and Jensen 1987, Jensen and Hodgson 1987). As a result, the research focus has shifted toward developing new techniques for exploiting spatial information (Sun and Wee 1982; Woodcock et al. 1988a, 1988b; Lee and Philpot 1991; Yuan et al. 1991; Franklin and McDermid 1993). Woodcock and Strahler (1987) examined various cover types at SPOT and Landsat TM resolutions (Table 5) and found the local image variance to be high for forested and urban/suburban cover types. They suggested that texture, context, and mixture modeling be incorporated into information extraction techniques for these data. Of particular focus has been the development of new classification algorithms that incorporate textural and contextual measures, as discussed in the previous section. However, to date, the development of more sophisticated sensors and more complex classification techniques, be they supervised or unsupervised, parametric or nonparametric, spectral, textural, contextual or knowledge-based, has not led to satisfactory results on a repetitive basis (Marceau 1992). Terrestrial and photogrammetric measurements remain the standard for the majority of scientific and operational mapping projects. For this reason, a more detailed examination of surface features and their relationship to remote sensing spatial resolution is required.

The Modifiable Areal Unit Problem (MAUP)

Remote sensing images represent comprehensive spatial samples of terrain or other surfaces, and each pixel contains the integrated radiant flux for the surface features (e.g., trees, shrubs, ground cover, soil, and shadows in a forested environment) over an area corresponding to the spatial resolution of the sensor. Based on traditional remote sensing methods, it is implied that there is a strong and predictable correlation between the measured radiance and the surface features of interest. However, surface features possess different sizes, shapes, and spatial distribution, as well as spectral characteristics, which would indicate that for an arbitrary sampling grid such as that imposed by remote sensing systems, there is really no intrinsic geographic meaning to the spectral measurements recorded (Marceau et al. 1994b). Arbitrary sampling does not necessarily provide a suitable model for nature. In nature, scales of phenomena are dictated by the physical laws that dominate at each level and, rather than being arbitrary, tend to concentrate around discrete levels that may be far apart (Klemes 1983). It has also proven difficult to apply statistical image analysis techniques to spectral data acquired in this manner (i.e., using an arbitrary sampling grid) in order to extract meaningful information with a high degree of accuracy and repeatability. This observation is embodied in the modifiable areal unit problem (MAUP), as described by Openshaw (1984).

The MAUP is actually comprised of two sets of interacting problems, the first associated with spatial scale and the second with spatial aggregation (Openshaw 1984). For example, a variety of different analysis results may be obtained as the same areal data are iteratively grouped into larger areal units for analysis. Hence, analysis results are dependent on scale. Second, at any given spatial scale, data may be aggregated in a variety of ways. In essence, the scale problem indicates a failure to understand the processes or phenomena that occur at different scales and the aggregation problem indicates a failure to discriminate the objects of geographical enquiry (Dudley 1992). In studies of spatial data, including remote sensing studies, interpretation of those data is a scale- and aggregation-dependent phenomenon. Upon examination of the scale and spatial aggregation problems in remote sensing, Marceau (1992) found that there is a scale and aggregation level that is specific to the discrimination and analysis of each ground feature of interest in the scene. It is therefore necessary to identify an optimal spatial resolution for analysis. As defined by Marceau et al. (1994a, p. 106), optimal resolution is, "The spatial sampling grid corresponding to the scale and aggregation level characteristic of the geographical entity of interest." This approach will require a multiscale sampling design for data acquisition, analysis, and interpretation.

Selecting an Appropriate Spatial Resolution (Scale)

Two assumptions identified by Duggin and Robinove (1990) as being implicit in remote sensing data acquisition and analysis are that data be (i) collected and (ii) analysed at an appropriate scale to detect and quantify the features of interest in the image. These are requirements for an adequate exploration of the spatial character of the surface features and are intended to ensure that spectral characteristics or classes in the image correspond to information classes required by the user. To select an appropriate scale for data acquisition and analysis, the spatial structures of the ground surface features and of the images must be understood. Specifically, it is important to understand the manner in which images of a scene change as a function of spatial resolution (Woodcock and Strahler 1987). A suitable scale for observations is a function of (i) the type of environment being studied and (ii) the type of information required (Woodcock and Strahler 1987), although suitable consideration must also be given to the techniques used to extract information from the remotely sensed data.

Spatial structure of an image is determined by the relationship between the size of the objects in the scene and spatial resolution. There are two approaches that can be taken to examine the spatial structure of a scene (Marceau 1992). First, detailed field information characterizing the spatial structure of the surface features can be collected and compared to the information content of remote sensing data collected at a variety of spatial resolutions in order to determine the influence of surface features on information extraction. It has been shown that when spatial resolution is considerably smaller or larger than the surface feature of interest, it is likely that sample pixels for these features will exhibit high spectral variance; if the spatial resolution samples the appropriate mixture of feature attributes, spectral variance will be at a minimum (Woodcock and Strahler 1987, Marceau et al. 1994a). A reciprocal approach consists of modeling scenes of a known structure (discrete elements distributed over a continuous surface) to derive the spatial structure they portray in digital images acquired from them (Jupp et al. 1988). Models have been used to simulate a forest scene in order to determine optimal resolution (Li and Strahler 1985, Woodcock and Strahler 1987); however, these are generally oversimplified, as they usually assume that scenes are composed of objects arranged in a mosaic that completely covers the area or objects that are distributed on a continuous background.

Various tools have been developed to measure the spatial structure of digital images. For example, the spatial structure of images has been investigated using spatial autocorrelation (Craig and Labovitz 1980, Campbell 1981, Labovitz and Masuoka 1984), using one- and two-dimensional variograms (Woodcock and Strahler 1985), by plotting local variance as a function of spatial resolution (Woodcock and Strahler 1987), by determining the minimal spectral variance of a class (Marceau et al. 1994a), and by overlaying grids on aerial photographs and counting the number of land-use categories that occur in each grid cell (Simonett and Coiner 1971). Using grids of different sizes, Simonett and Coiner (1971) demonstrated that the complexity of the scene and spatial resolution determines the number of pixels that contain multiple land-cover types. Woodcock and Strahler (1987) assessed spatial structure by graphing the local variance in images as a function of spatial resolution. The peak of the variance generally occurs at a slightly smaller spatial resolution than the size of the element in the scene. It was noted by Woodcock and Strahler (1987) that local variance for a forest stand decreased below spatial resolutions of 3–4 m. This indicated that assumptions of spectral per-pixel classifiers were once again valid, but only on a per-tree basis rather than on a stand basis. Marceau et al. (1994a) used minimum spectral variance to define the optimal spatial resolution for each class and found that stand spatial and structural characteristics were the dominant features contributing to the optimal spatial resolution.

An alternate approach utilizes the semivariogram, which originates from the theory of regionalized variables developed by Matheron (1963). The semivariogram is used to measure the spatial dependence of neighboring observations for any continuously varying phenomenon. Hence, it is a technique that can be applied to spectral data (radiance), a phenomenon for which position in time and space is known (Woodcock and Strahler 1983). In this manner, spatial variation in images can be examined in relation to ground scene and sensor parameters (Woodcock et al. 1988a).

The semivariogram plots semivariance against spatial separation along a given relative orientation (Fig. 4, Table 15), and provides a concise and unbiased depiction of the scale and pattern of spatial variability (Curran 1988). In essence, it measures the correlation between pixels at successively greater distances and will demonstrate a peak in variance when pixels become independent of one another. This peak in variance is known as the 'range of influence' of the semivariogram. The semivariogram has proven useful in remote sensing because it enables researchers to relate some of the descriptors of the semivariogram to the spatial characteristics of the scene.

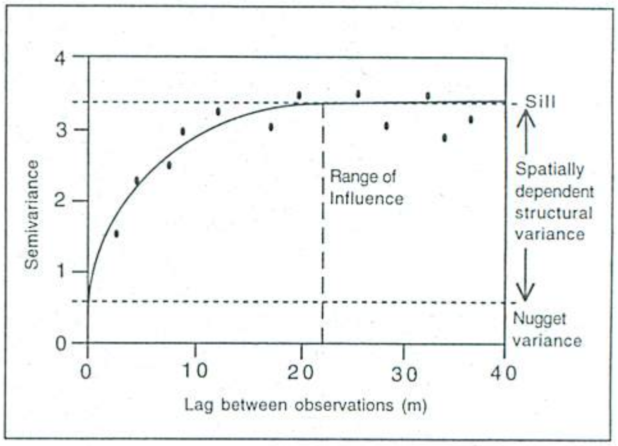

Figure 4. The shape and description of a typical variogram.

Table 15. Terms and symbols used in the description of the semivariogram.

Term	Definition
Lag	Distance (and direction in two or more directions) between sampling pairs.
Sill	Maximum level of semivariance.
Range	Point on lag axis where semivariance reaches a maximum. Places closer than the range are related; places further apart are not.
Nugget variance	Point where the extrapolated relationship between the two variables intercepts the semivariance axis. Represents spatially independent variance.
Spatially dependent structural variance	Sill minus nugget variance.

(*Adapted from* Curran 1988.)

For example, the range, which defines the distance at which pixels are not spatially related, provides a measure of the size of the elements in the scene and has been suggested as a useful indicator in selecting the optimal spatial resolution for discriminating the features embedded in the image semivariogram (Curran 1988; Woodcock et al. 1988a, 1988b). Woodcock et al. (1988b) calculated variograms from real digital images and found: (1) the density of coverage of objects in the scene affects the height of the variogram; (2) object size affects the range of influence of the variogram; and (3) the variance in the distribution of the sizes of objects affects the shape of the variogram (i.e., as variance increases the shape of the variogram curve becomes more rounded).

Atkinson and Danson (1988) used semivariograms to measure spatial dependence in coniferous and oak (*Quercus* spp.) plantations. They found the range of the variogram was related to stand age and species, and were able to determine the optimal spatial resolutions for even-aged stands. Cohen et al. (1990) found the ranges for 1-m spatial resolution data were related to the mean tree canopy sizes of the stands. In contrast, semivariograms based on 10-m and 30-m pixels contained significantly less useful information. However, Bowers et al. (1994) were able to measure differences in semivariogram characteristics for thinned, unthinned, damaged, and undamaged balsam fir (*Abies balsamea* [L.] Mill.) stands using SPOT panchromatic data. These spatial characteristics were superior to spectral measures for examining damage incidence and forest structure (stems/hectare). Lathrop and Pierce (1991) used semivariogram analysis of forest canopy transmittance measurements and Landsat TM near-infrared/red ratio data to examine the scale of variation in canopy structure and to determine the most appropriate scale at which to sample transmittance. This analysis depicted the similarity between the two sets of data with respect to spatial auto-correlation structure. The range of the semivariogram was used to aggregate the Landsat TM and attenuation data sets for regression analysis by averaging segments of the transect (where segment length equals semivariogram range). It was discovered that by averaging within an appropriate landscape unit (e.g., hillslopes), large scale variability of measurements (due to small forest gaps) was reduced.

Remote Sensing at Multiple Spatial Resolutions (Scales)

An important question surrounding the selection of an appropriate spatial resolution was suitably phrased by Openshaw and Taylor (1979, p.143), "What objects at what scales do we want to investigate." Information is a scale-dependent phenomenon. Often it is assumed that just one scale will provide the desired results to a complex problem. This assumption requires examination and must be used with caution since the data in a remote sensing image are nonhierarchical in a classification sense (Everett and Simonett 1976). For example, Marceau et al. (1994b) examined a natural forest environment at a variety of scales and concluded that there is no unique spatial resolution at which all geographic entities could be discriminated. Everett and Simonett (1976) described the environmental modulation transfer function to formalize the notion that applying a single resolution to many environments will not produce a uniform class of information for all environments. Environments are too complex over space and time to be reduced to a single spatial resolution (scale). Spatial resolutions (scales) are frequently imposed on nature, often without necessarily knowing if those scales reflect natural patterns/forms/

functions. However, as researchers into the character of nature, we must search for those scales of nature that exist and try to understand their interrelationships and patterns (Klemes 1983).

In many remote sensing studies, it has been observed that there are dramatic inconsistencies in the classification results between one class and another, thereby leading to poor overall accuracies. Intuitively, classes that demonstrate poor accuracies have not been sampled at an appropriate resolution or they are not separable at any particular resolution (i.e., the class label does not represent the spatial structure of the class). It has been observed that the utilization of a single scale of remotely sensed data tends to cause the image to operate as a spatial-frequency filter (Clark 1990). Patterns higher in frequency than the spatial resolution of the data and lower in frequency than the size of the scene are inherently filtered out. In this case, only a subset of the natural variation of the surface is captured. Remote sensing spatial resolutions (scales) must be matched to the frequency of variation in nature, variations which do not occur at a single spatial resolution. Clark (1990) used multiple scales to map ice-flow landform features that resulted in radically new interpretations of the dynamics and behavior of the Laurentide Ice Sheet. Analysis of multiple scales (a geographer's strength according to Stone [1972]) may be a more appropriate approach for identifying forest classes from remote sensing data.

Summary

From the preceding discussion on spatial resolution (scale), it is evident that more attention must be paid to the attributes of surface features and how these attributes are characterized in image data. Duggin and Robinove (1990) expressed concern that although remote sensing analysts are generally very analytical with regard to the interpretation procedures applied to quantitative analysis of digital image data, there is less attention paid to image data selection, sensor design and calibration, and optimal environmental conditions for data acquisition. In fact, there is generally a poor understanding of the assumptions involved in linking ground-level attributes with the spatial and spectral measurements recorded by the sensor. This must be done at a detailed level to isolate and understand the major components contributing to spectral reflectance at smaller scales. With this knowledge, sampling systems can be designed to optimize the segregation of various levels of features in a scene. This approach identifies a requirement for characterization of surface features at various spatial resolutions (scales) in order to determine the effect of spectral and spatial aggregation on surface feature extraction. Analysis of high spatial and spectral resolution data will improve our understanding of the spatial and spectral components of a forest canopy and their relative effects.

CONCLUSIONS

Currently, aerial photographs, dated map products, and intensive field surveys provide the majority of information for forest mapping and monitoring and, in turn, for management and planning. However, remote sensing of forest resources offers potential for assisting these traditional methods for a variety of mapping scales. As sensor technologies and data-analysis techniques improve, the potential for remote sensing data to provide information on forest ecosystems and ecosystem processes from local to global scales will improve. Currently, data from satellite sensors, such as Landsat TM and SPOT, are used operationally to provide generalized forest-cover mapping. However, this technology is used only by a few select government agencies and consulting firms. For remote sensing potential to be fully realized, this type of technology must become more accessible to forest managers.

In this review, the requirement for detailed forest ecological data in support of integrated forest resource management has been identified. Traditional forest inventories for timber management are no longer sufficient as increasing demands are placed on forest resources. An integrated forest site management approach that incorporates the biotic and abiotic components of the ecosystem and their ecological relationships is required. This detail is necessary for multiuse planning for ecological sustainability and the maintenance of biodiversity, and for the derivation of more transparent site factors, particularly those related to growth and yield modeling and current forest management practices.

To simplify the myriad of forest and site parameters, as well as the energy processes flowing between them, a method of classifying forest ecosystems was developed. A forest ecosystem classification (FEC) (Jones et al. 1983, Sims et al. 1989) is a hierarchical classification scheme that is well developed for field evaluation of forest sites at the stand level, but is not practical for classifying forest ecosystems over large areas. A remote sensing method for classifying forest ecosystems for large areas, with a minimal amount of ground information, is required to extrapolate the FEC to large portions of Ontario's forests.

To evaluate the effectiveness of remote sensing data for forest ecosystem classification, a number of issues must be addressed. First is the suitability of the information classes for spectral classification. This requires an understanding by the analyst of all the different types of resolution—spatial, spectral, temporal, and radiometric. In particular, the information content of remote sensing images is a direct function of measurement scale, as determined by the spatial resolution of the sensor. Conditions must be selected that maximize the spectral separability between classes. However, as first emphasized by Townshend (1981), there continues to be a substantial need for basic research on the spatial, spectral, and temporal properties of many types of vegetation. Until these properties are better understood, it is difficult to determine optimal conditions for remote sensing data collection and subsequent analysis. Likewise, there is a need for increased understanding of the spectral properties of different ecosystem types at various spatial, and temporal scales. This will lead to the collection of remote sensing data at the appropriate spectral, spatial, and temporal resolutions for optimal ecosystem analysis and interpretation.

If it is determined that the information classes of particular interest are not spectrally (or texturally) separable, then they must be modified to more closely approximate the character of the data. However, FEC classes are based on ecological principles so it may be possible to assume that they represent distinct levels in nature. As an integrated unit of physiography, soils, climate, and vegetation, they may be unique at a particular level in a hierarchy that corresponds to a given spatial resolution. Also, the FEC is hierarchical, and presents greater opportunities for correlating remote sensing data at various scales with particular levels in the hierarchy.

Closely associated with this issue is the selection of remote sensing data with appropriate resolutions, particularly spatial resolution, for the extraction of forest ecosystem information. It has been argued in this paper that single spatial resolution (scale) remote sensing data are not sufficient to appropriately sample the scales that are encountered in nature. Although it is dependent on the variable being measured, surface parameters often exhibit multiple scales of variations and thereby portray different environmental controls and processes at different scales (McGwire et al. 1993). Therefore, the scale at which remote sensing data are collected and analysed is a significant controller on the relevance of the results. One cannot presume that a single arbitrary spatial resolution can satisfactorily sample the information categories that have been imposed on nature. As Paul Kopper wrote: "It is important always to keep in mind that we are students of nature, of forms not created by us, hence not subject to our control. To project human notions...on nature is not science" (*from* Klemes 1983, p. 1). Klemes (1983, p. 1) went on to argue that: "Levels of scale at which meaningful conceptualization of physical processes is possible are not arbitrary and their range is not continuous." Hence, surface features and aggregations of surface features may be recognized at different scales. However, it is logical that objects within a scene (or agglomerations of objects) can be discriminated at an appropriate spatial resolution that corresponds to their intrinsic spatial and spectral character (Marceau et al. 1994b). It is therefore more appropriate to operate under the assumption that multiple scales of remote sensing data are required, first to understand the nature of the scene, and second to extract useful information. The structural characteristics of the objects on the surface must first be modeled using high spatial resolution data. This will provide baseline information, through geostatistical analysis, for selecting the most appropriate resolutions for separating the objects and aggregations of objects in the scene.

A second consideration falls under the category of data improvements. This involves modifying the raw spectral data so that they are more suited to information extraction. An example of this type of data improvement is the generation of texture features from spectral data. This form of feature processing attempts to quantify the textural information within the spectral data, and may become more prevalent at higher spatial resolutions as stand structural characteristics begin to dominate the scene. Texture features provide additional information layers for classification. Another form of data improvement is the incorporation of ancillary data into the analysis process. Combining elevation data and its derivatives (e.g., slope, incidence angle) with spectral data in a classification is an example of this type of data improvement. Since these variables tend to be highly correlated with vegetation types (particularly in high-relief environments) they may prove useful for the discrimination of certain cover classes. These techniques often improve classification accuracy when compared to using spectral data alone.

Third, the testing of new classification algorithms, which incorporate textural and contextual information, may provide more accurate classification results than do traditional approaches. Also, classifiers that are not restricted by statistical assumptions are now available. These classifiers allow the analyst to incorporate a variety of data types (e.g., nominal, ordinal, interval, and ratio). This allows data integration from a variety of sources.

Based on this review, it is recommended that a systematic approach to forest ecosystem classification with remote sensing data be initiated. This should start with a detailed analysis of stand structural characteristics recorded at various levels of spatial aggregation. Second, data improvements in the form of feature processing (e.g., texture, principal components) and addition of ancillary variables is required to optimize class discrimination. Third, evaluation of nontraditional classification algorithms that incorporate spectral and spatial characteristics are expected to improve classification accuracies. It is anticipated that careful examination, testing, and evaluation of these three issues will provide reliable methodologies and approaches to forest ecosystem mapping at several levels or scales.

ACKNOWLEDGMENTS

This research was funded by a Centre of Excellence Grant from the Province of Ontario to the Institute for Space and Terrestrial Science. Funding for the printing of this publication has been made available through the Northern Ontario Development Agreement, Northern Forestry Program. The authors would like to thank Dr. Richard Sims of the Canadian Forest Service–Sault Ste. Marie for his thoughtful review of the original manuscript.

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