From need to product: a methodology for completing a land cover map of Canada with Landsat data

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Abstract

In spite of its very large territory and the best Landsat archive in the world, so far Canada has made very limited use of Landsat data for land cover mapping purposes. The primary difficulty has been the prohibitive cost of information extraction, in addition to the earlier (and now overcome for Landsat 7 ETM+ data) high costs of data purchase. The solution to this remaining obstacle lies in decreasing the cost of Landsat data processing and analysis while ensuring high quality of the extracted information. In this paper, we present an efficient and effective approach to mapping land cover of Canada from Landsat Thematic Mapper data (single- or multi-satellite). Its key feature is increased ratio of computer to human analysis, and automation for high data volume/large area processing. However, it is essential that the final product quality not suffer because of the stronger reliance on computer processing, thus the algorithm performance becomes critical. We describe the overall approach, discuss key challenges, explain the principles behind key algorithms developed to respond to the challenges, present evidence demonstrating the effectiveness of these algorithms in boreal landscape setting, and consider implementation issues. With a processing system developed to handle large numbers (tens to hundreds) of Landsat scenes which incorporates most of the algorithms discussed here, the stage is nearly set for large-scale processing leading to Landsat-based land cover classification product(s) for Canada.

1. Introduction

1.1 Background

Land cover is arguably the most important characteristic of the land surface, from the environmental as well as societal perspectives. Most ecosystem processes strongly depend on, and in turn influence, land cover and its attributes. Similarly, land use is strongly conditioned by land cover. Since land cover varies in time and space, mapping approaches have been used in the past to obtain information on its distribution and spatial variation. With the advent of aerial photography this process has become more efficient, and methods for large area applications have been developed (e.g., Anderson et al., 1971). Although aerial photography has continued to be the medium of choice for specialized resource management applications such as forest inventories (e.g., Leckie and Gillis, 1995), for general land cover mapping its widespread use was dampened by the substantial cost of data acquisition and interpretation coupled with relatively slow rate of land cover change and the perceived low need for such information over large areas, especially outside of those directly occupied or exploited for human uses.

The perception of the need for land cover information has changed with the recognition of the reality of global change. The accelerated changes in land cover and use in various parts of the world, the regional to global nature of the key biogeochemical processes which depend strongly on land cover, and the realization that we must respond to these trends to preserve habitability of the Earth has brought about strong interest in land cover characteristics, its spatial distribution and temporal dynamics, and the relation of land cover to economic and social activities. Satellite observations have become the major means of obtaining data on these aspects of land cover. Although digital techniques for extracting land cover information have been explored since the late 1960s, the generation of maps over large areas had to await progress in (i) the collection of good quality and affordable data, (ii) processing methods that would produce data sets with sufficiently high quality (signal to noise ratio) to yield land cover information of interest, and (iii) adequate computing power (Cihlar, 2000).

A combination of the above factors led to the use of ‘coarse’ (thousands of meters) resolution satellite data as the initial thrust, with pixel sizes of 8 km to 1 km, globally or regionally (Loveland and Belward, 1997; DeFries et al., 1998; Hanson et al., 2000; Loveland et al., 1995, 2000; Cihlar et al., 1997, 1999). However, it was realized that for many purposes, these maps do not provide sufficiently detailed information because land cover (and change) varies over short distances and this patchiness cannot be captured by coarse resolution data. Albeit to a much a lesser degree, mixed pixels remains a problem for higher resolution (~0.3 km) data from sensors such as the Moderate Resolution Imaging Spectroradiometer (MODIS), Medium Resolution Imaging Spectrometer (MERIS) and Global Land Imager (GLI). Thus, parallel interest has grown in the use of ‘medium’ resolution (tens of meters) satellite data, especially since the late 1980s when both the methodologies and computing capabilities were well developed. Good examples of successful mapping activities are the US National Land Cover Data Set (NLCD; Vogelmann et al., 2001b) and Gap Analysis Project (GAP; Jennings, 1995) which have succeeded in assembling the necessary financial and human resources to map the conterminous US from Landsat Thematic Mapper (TM) data. In general, however, the widespread use of medium resolution data for land cover mapping has until recently been hampered by the high cost of satellite data.

As a vast country with small and very unevenly distributed population, Canada has long been prime candidate for land cover mapping with satellite data. Realizing the importance of satellite measurements for national environmental applications, since 1972 the Canada Centre for Remote Sensing has maintained a program of systematic reception and archiving of Landsat Multispectral Scanner, Landsat TM, and SPOT haoute resolution visible (HRV) data over the Canadian landmass, and in the process established the most comprehensive archive of any country in the world. Nevertheless, these data have not yet been used systematically for land cover mapping at the national scale. The main impediments have been the cost of data and, since the mid-1990s, the cost of information extraction. In addition, until recently insufficient attention has been paid to the analysis of the feasibility and key technical issues associated with such a project.

With the cost of medium resolution satellite data no longer an obstacle and in view of inexpensive data Landsat TM sets available for Canada from several projects (e.g., the national Landsat 7 orthoimage project - http://maps.nrcan.gc.ca/main.html; the global Landsat TM coverage for 1990 (Dykstra et al., 2000) and a similar one planned for 2000), the main remaining questions concern the type of product(s) required at the national scale and the appropriate information extraction methods. Regarding the latter, both accuracy/robustness and cost are of concern. In practical terms, reducing information extraction costs translates to increasing the computer analysis/human analysis ratio. Significant progress has been achieved over the last several years in improving the efficiency and robustness of the major analytical steps, and these improvements may be used to advantage in a national scale project.

The intent of this paper is to examine the methodological feasibility of completing a land cover map of Canada from Landsat TM data. The following areas are examined: information and product(s) required for the main present applications; data processing and analysis scheme; key technical issues and candidate algorithms to resolve these; accuracy assessment considerations; and implementation aspects.

1.2 Information needs

Most of the applications considered below require land cover information in the form of a discrete set of characteristics associated with each parcel of land. In this case, the mapping legend will consist of a set of non-overlapping classes to which the individual pixels are assigned. This is the mapping issue addressed in this paper.

Land cover and use assessment. Land cover is the key environmental information required for many management and research purposes. Resource planning and management decisions require knowledge of the current status of land cover and its changes with time. Such information is used for planning purposes, inventories, research studies, communication with the public, education, and for other purposes. In the context of sustainable development, land cover is an important indicator for assessment and reporting. The classification legend and level of detail vary depending on intended use, from few, fairly general classes to many, highly detailed cover types. For example, national reports to the UN Framework Convention on Climate Change are expected to contain data on afforestation, reforestation and deforestation, each of these terms being precisely defined (FCCC, 1999). Land cover is also the main input into the mapping and monitoring of land use (Cihlar and Jansen, 2001), the primary environmental parameter for sustainable development.

Carbon balance modeling and reporting.

Carbon budget modeling is based on the ability to quantify controls on carbon assimilation, respiration and removal due to disturbance (e.g., Chen et al., 2000). All three factors are related to the amount of carbon present in soil, decaying organic matter and live biomass. Standing biomass can be estimated from crops and shrubs as well as forests up to a saturation point around 50 T/ha through the use of nadir optical reflectance and a priori knowledge of land cover (Fazakaz et al, 1999; Myneni et al, 2001; Van der Meer et al. 2001). These estimates can often be refined if species or crop type maps are available. Soil, necromass and litter carbon pools are typically estimated by inference related to land cover or species.

Land cover information is required at different levels. The type and extent of woody vegetation, grassland, cropland, or shrubland may be inferred through classification of multi-date imagery together with surface plots of known cover type (Franco-Lopez et al., 2001). This land cover information, when enhanced using GIS databases to produce maps of land use, can be related to nutrient inputs and sources of atmospheric pollutants (Aber et al., 1997) and greenhouse gases (e.g., Grewe et al., 2001) that may impact carbon assimilation. Information on species composition is important to quantify carbon uptake through photosynthesis. Severe drought, storm damage, insect or disease induced foliage loss, forest burns and harvest may be evident as land cover changes (Cohen et al., 1998; Fraser et al., 2000). On longer time scales, remote sensing may serve to relate canopy closure to stand age and hence stand level assimilation rates. Similarly, the pattern of land cover in a region may serve as an index of functional diversity (Griffiths and Lee, 2000). Finally, comparison of current and historical land cover may serve to indicate geographic shifts in functional vegetation complexes related to population or climate impacts (Chuvieco, 1999).

Forest inventory. Forest inventories in Canada are updated in an approximately ten-year cycle (Gillis and Leckie, 1993). Forest polygons stored in a geographic information system (GIS) are normally created from digitization of manually interpreted air photographs (Gillis and Leckie, 1993). The forest management unit information stored in the GIS is based on a complex set of forest conditions. The criteria to delineate the forest management unit areas are the presence of homogeneity of forest characteristics such as species assemblages, stand density, crown closure, and development stage (Leckie and Gillis, 1995). As the inventory is updated incrementally, the forest inventory information is typically collected in different years. The scale of photographs utilized by forest managers commonly ranges from 1:20,000 to

1:60,000, corresponding to an equivalent scale resulting from Landsat imagery of approximately 1:250,000 (Wulder, 1998). As a result, these different sources yield different inventory information. The strengths of classifications developed from satellite remotely sensed data include large area coverage, timely nature of collection and distribution, access to data relating past conditions, and the ability to consistently apply classification techniques. The landscape - level view is important to a range of stakeholders from forest managers to ecologists as the conditions evident at a particular location can be placed in a larger context. The large area coverage and classification to a single vintage is also valuable for calibrating forest inventory data obtained from air photos.

Biodiversity. Fine resolution satellite data are increasingly important in biodiversity research and conservation efforts (Kerr, 2001; Kerr et al., 2001). The best known such initiative is the Gap Analysis Program (GAP), currently underway throughout the United States (Scott, 1993; Scott et al, 1996; Crist, 2000). The principle that drives GAP is simple: knowledge of the distribution and concentration of biodiversity is required to allow conservation efforts to be focused toward areas of highest risk. Since biodiversity data are rarely sufficiently comprehensive, detailed classifications are used to enable spatial extrapolation of *in situ* observations. To be effective, such extrapolation should be based on detailed information regarding the distribution of species. Landsat TM data, in conjunction with other spatial data, have sufficient resolution to map the relevant differences in cover and habitat, in some cases down to a species association level (e.g., Homer et al., 1997). The methods exploited in GAP range from visual interpretation to fully digital image processing methodologies supported by the collection of high spatial resolution video data (Slaymaker et al. 1996). To link this information to individual plant species, additional field data are required on the regional and local composition of plant associations.

Water quality modeling. Land cover plays a key role in regulating the quality and quantity of surface water, especially regarding its suitability for direct human or industrial consumption. Surface water pollution is an issue in areas with intensive land use where opportunities for chemical contamination of surface water exist. In the last several years, methods have been developed to combine detailed land cover maps with other geospatial data types to model potential problems in surface water pollution (e.g., Fraser et al., 1998; Jones et al., 1997). Outputs of these procedures have been employed for watershed management (Heggem et al., 1999), and they are directly relevant to ground water pollution problems that are beginning to appear in densely populated areas of Canada with mixed land use. In this application, the required information concerns general land cover types (e.g., forest, cropland, urban) with more detail on forest conditions. Spatial resolution of 30 m is adequate, as it enables detection of narrow bands of vegetation along streams. In regions surrounding densely populated areas, detailed land cover data can be crucial for modeling water quality impacts of pollutants such as those generated through industrialized agricultural activities.

2. Overall approach and methodological issues

The above information requirements indicate that the specific land cover information requirements vary among applications, from fairly general classes to specifically defined types and also from relatively few to many classes. FCCC reporting is an example where few but specifically defined classes with high accuracy are required, while biodiversity applications need detailed (species-specific if possible) information but are more tolerant of classification errors. Also, a single classification legend may satisfy many users but not all. The above factors suggest a potential need for several mapping products over the same geographic area. On the other hand, the relatively high costs, efficiencies of scale, and the possibility to share the mapping task argue for a single mapping exercise.

The proposed methodology addresses the above dilemma in two ways, by (i) dividing the sequence of operations into two stages and (ii) permitting the extraction of all land cover type information contained in the satellite data. The first stage is independent of the specific classification legend employed and can therefore be carried out through bulk processing. If in addition the processing algorithms can be automated, the costs for this phase of the mapping task will be relatively small. This stage contains (Figure 1) data calibration, atmospheric correction, ways to deal with clouds and other atmospheric contamination, and an initial classification resulting in a dense (super-clustered) data set, which may efficiently be labeled. The second stage is concerned primarily with 'labeling'

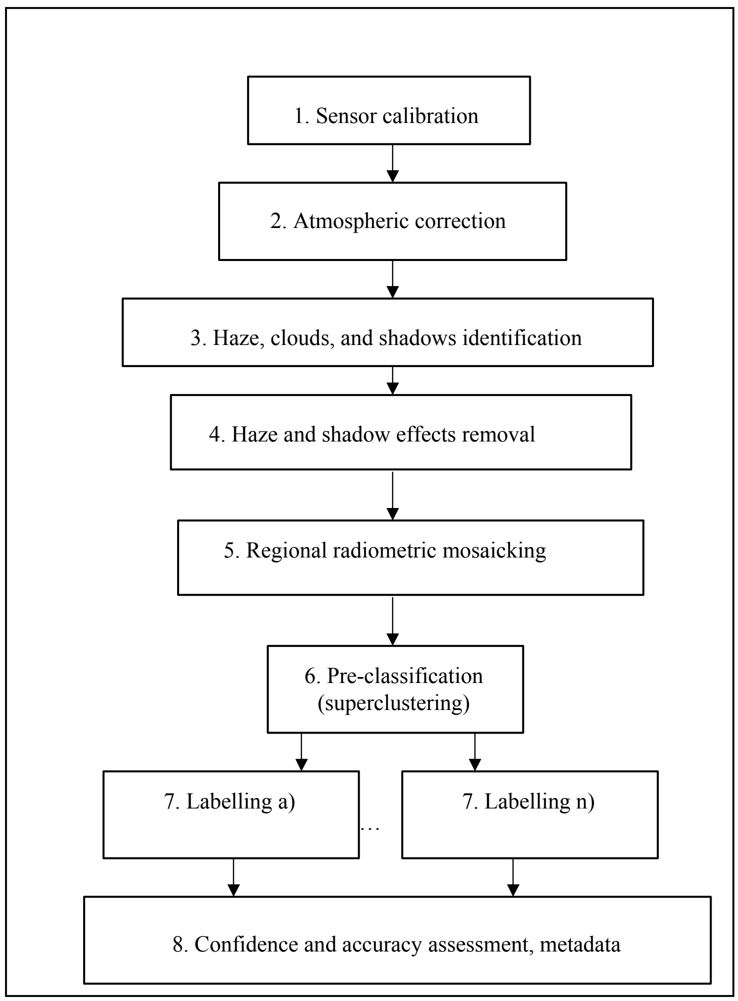

Figure 1. Overall data processing flowchart

and associated operations, i.e. assigning spectrally distinct groupings of pixels to specific categories of the mapping legend. It is at this stage that the issue of one or more products can be dealt with, as discussed below. In this paper, we describe an approach that retains all or most of the land cover information available in the TM data, thus permitting the mapping of detailed classes. This methodology is thus fully applicable to mapping applications involving fewer classes, with appropriate simplifications leading to increased efficiency and reduced cost. It should also be noted that the procedure is fully applicable to data from other sensors with a comparable information content to Landsat TM.

In principle, the required land cover information may be derived from satellite data in different ways. The most commonly used approach to date has been direct classification using various image analysis techniques; this approach is represented here by unsupervised classification and analyst's labeling. A more recent strategy is to derive intermediate products more directly related to the observed spectral reflectance and then transform these into land cover according to the known properties of different land cover types. We have been developing a reflectance model-based solution as described below, but other algorithms have been used with multitemporal data (e.g., DeFries et al., 2000; Fernandes et al., 2002). Probably the fundamental methodological issue to be overcome in either case is that the desired number of land cover categories is higher than the number of independent observations (spectral bands), i.e. the problem is underconstrained.

A trade-off must be addressed in selecting the satellite scenes for national land cover mapping. On the one hand, a narrow acquisition window is desirable to minimize the temporal uncertainty in the thematic content. On the other hand, atmospheric conditions (i.e. cloud cover and haze) limit the probability of acquiring a 'clear' scene at a given orbital pass. US experience with the North American Landscape Characterisation (NALC) and the Multi Resolution Land Characterisation (MRLC) programs (EPA, 1993) indicates that an acquisition window encompassing at least 3 consecutive summer seasons (typically June 15 – August 31) is required to ensure that a complete coverage with a maximum allowable level of 15% cloud cover is achieved. For Canada, with the preferred 1 July – 31 August imaging period a temporal window of 3-5 years may be required to obtain images with <~10-20% cloud cover that are suitable for land cover mapping (see also Leckie, 1990). The mapping methodology must thus be able to cope with different dates of the source images, including images from different TM sensors.

2.1 Sensor calibration and atmospheric corrections

The first two processing steps (Figure 1) are fairly conventional and algorithms are available for routine use (Vogelmann et al., 2001a). A possible sensor- related issue is the intercalibration of data from different years or TM sensors. Thus, information on sensor degradation and on calibration differences among sensors is needed to obtain radiometrically uniform data sets (Masek et al., 2001). Based on recent work with Landsat 7 such information is, or is becoming, available (Teillet et al., 2001).

For clear sky, algorithms have been developed that are capable of reliable radiometric corrections for Rayleigh and uniform Mie scattering. The main challenge is the spatially variable aerosol optical depth resulting in differential Mie scattering. Previously developed techniques (Teillet and Fedosejevs, 1995; Liang et al., 1997) all assume that these effects have low spatial frequencies and thus the variation within a scene may be estimated from a limited number of sites. However, such assumption is not valid for most clouds or for haze. Since these two effects are the strongest noise source in the Landsat data, other ways are needed to deal with them as described in the following section.

In the procedure described here, radiometric mosaicking (step 5, Figure 1) ensures consistency among the component scenes. Since this step is required in any case, atmospheric corrections are, in principle, unnecessary if interactive labeling is employed in step 6 (Figure 1). However, they are desirable even if the scenes to be used have similar aerosol characteristics. The reason is that the atmospheric corrections properly account for differences in the solar zenith angle and possible differences in the spectral properties of individual channels (in case of different sensors). Accurate atmospheric corrections are very important if a model-based approach is employed in step 6.

2.2 Within-scene haze detection and removal

While extensive literature exists on atmospheric theory and potential correction, the number of studies that deal with the practicality of compensating for spatially varying haze is rather limited. During the extension of the Tasselled Cap (TC) transform to Landsat TM, Crist and Ciccone (1984) observed in visual inspection of the 4th component that its dominant response appeared to be to atmospheric haze. Subsequently, Richter (1996) used a simplified rendition of this component as the basis of an overall correction methodology but only applied it to a single TM sub-scene. Du et al. (2002) employed wavelet transform and multiple images of the same scene based on the observation that haze tends to obscure high spatial frequency variations in the recorded signal. Other approaches rely on locating 'dark targets' over the scene and using these to estimate local aerosol optical depth. These points are then used as seeds to generate a low frequency 'haze' mask that is oversampled at the pixel level (e.g., Liang et al., 1997).

For high-volume processing at a national scale, a haze compensation methodology is essential and should have the following attributes. First, it should be image-based since ancillary atmospheric information (aerosol type and optical depth) is very limited for Canada. Second, it should be robust, i.e. effective and consistently accurate for a broad range of haze conditions. Third, when attempting to remove the effect of haze it is sufficient to do relative compensation for varying levels of haze within a scene and not absolute ‘correction’, although in this case the corrected pixels will not be suitable for model-based application.

Recent work at CCRS has led to the development of a Haze Optimized Transform (HOT) that provides superior performance in the detection of haze compared to the TC transform (Zhang et al., 2002). It is based on the fact that visible bands exhibit highly correlated response to a wide range of thematic classes under clear sky conditions but differing levels of radiometric sensitivity to haze. In practical application, the haze-free/clearest regions of a scene are visually identified and used to define a ‘clear line’, i.e. the correlated band response to thematic (land cover) variation. HOT then measures the orthogonal displacement, in the selected visible spectral space, of each pixel from this line using the following equations:

$$HOT = B_1 \sin\theta - B_3 \cos\theta,$$

where B_1 and B_3 are the TM band 1 and band 3 gray levels respectively, and θ is the slope of the regression line in the band 1 vs. band 3 space. The value of θ is determined from a sample of highly correlated pixels (between B_1 and B_3) in the selected clear areas of a scene. The overlay of HOT values, computed for each pixel, then characterizes the spatial distribution of haze contamination.

A HOT image mask alerts the user that certain pixels are contaminated even if this effect is not evident from a visual inspection of the scene. Furthermore, by comparing the trend of increasing histogram lower bound with increasing HOT values, radiometric adjustment levels can be estimated automatically for each visible band. In essence, the gray level adjustment for a pixel is the difference between the lower bound of its relevant histogram and the histogram for pixels in the reference clear area of the image. The success of the removal depends on the degree of the initial contamination. While all affected pixels are flagged, only low contamination can be corrected for (Guindon and Zhang, 2002).

The HOT algorithm is flexible and has been found effective for Landsat MSS, TM and ETM sensors (Guindon and Zhang, 2002). Figure 2 illustrates an example adjustment of a partially obscured TM image of the Ottawa area. Zhang et al. (2002) provide detailed information on HOT characteristics and performance.

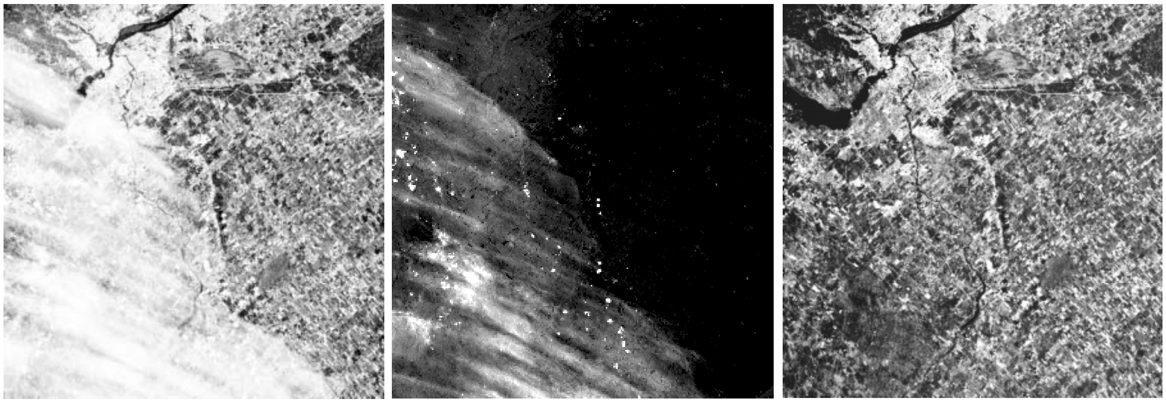

Figure 2. Example of the application of the Haze Optimized Transform. The left panel shows the input TM3 image, the central panel the haze overlay and the right panel the adjusted TM3 product.

2.3 Inter-scene radiometric normalization

One of the most labour- intensive activities in land cover mapping is the class labeling process (step 6, Figure 1). It is therefore desirable to merge scenes into regional image mosaics and then to treat these mosaics as image entities rather than separately classify each scene. For example, NLCD employed non-overlapping mosaics containing portions of 16-20 scenes (Vogelmann et al., 2001b).

A key step in generating regional mosaics is the radiometric normalization of scenes to a common scale in order to achieve a 'seamless' output. Typically, the clearest scene is visually selected as a reference and all other scenes are successively normalized to it as they are entered into the mosaic. Such radiometric 'balancing' is typically achieved through linear regression analyses of gray level scattergrams for pixels in image overlap regions (i.e., scene to be entered into the mosaic and the current mosaic; Guindon, 1997). This in turn leads to the definition of a single set of normalization coefficients that are then applied to all pixels of the incoming scene (e.g., Merson, 1981; Horii et al, 1984). The definition of this scaling can be adversely affected by spatially-varying haze, the presence of clouds, and temporal surface cover changes. While the area affected by haze can be identified with HOT and then eliminated from computing the normalization coefficients (see below), clouds and surface cover change are readily detectable as outliers in the scattergram of the overlapping area. Methods for the automatic detection of these pixels have been developed based on clustering (Guindon, 1997) and principal component approaches (Du et al., 2001).

A complication in the preparation of regional mosaics is the accumulation of errors from the addition of successive scenes to the mosaic, which depends on the order of scenes included in the mosaic (Guindon, 1997). To overcome this problem, Du et al. (2001) developed a radiometric normalization for image mosaics (RNIM), which permits an overall adjustment among the scenes included in the mosaic. The basic relationships are:

$$gain(m) = \frac{\sigma_{(m-1)B}}{\sigma_{mA}} \times gain(m-1) = \frac{\sigma_{mB}}{\sigma_{mA}} \times gain(1) \times ... \times gain(m-1); \qquad [1]$$

$$offset(m) = \mu_{(m-1)B} - \frac{\sigma_{mB}}{\sigma_{mA}} \times gain(1) \times ... \times gain(m-1) \times \mu_{mA} + offset(m-1); \quad [2]$$

where A and B refer to slave and master scenes, respectively; μ and σ are the mean and standard deviation for time-invariant targets/pixels in the overlapping area; and m refers to the m^{th} scene in the mosaic. An important feature of RNIM is that an overall adjustment is made after computing all gains and offsets, by normalizing these to the lowest gain (thus setting all gain values to 1.0 or higher) and by setting the lowest offset (if negative) to 0. These steps ensure that no loss of information occurs in the mosaicking process, and their importance has been ascertained in a practical application (Beaubien et al., 1999; Beaubien et al., 2001). RNIM has other important features. First, it provides a quantitative measure of the success of the radiometric adjustment. Second, the order of entering the scenes in the mosaicking process does not matter in RNIM, as long as all the scenes to be mosaicked are available at the outset. Third, RNIM makes changing an individual scene in the mosaic very easy, because only its overlapping areas with the adjacent scenes need to be considered and the overall adjustment recomputed. Fourth, if a mosaic consists of a grid of images two passes are required, first normalizing along rows and then along columns, in the second pass considering each row as one image entity. Finally, while in principle all the RNIM steps can be automated, at the present analyst input is required at three stages: selection of images to be mosaicked, confirmation of the selected characteristic pixels (i.e., those upon which the computation of gain and offset are based), and visual quality control of the final output.

Time invariance of reference targets in the overlapping area is a necessary condition for radiometric adjustment. In Canada, such surfaces exist in most images provided that they have been obtained in similar phenological periods and are cloud- and haze- free. In an effort to meet these conditions, the time window may have to be enlarged in specific cases.

2.4 Classification

Image classification has long been subject of remote sensing research. Two basic approaches, supervised and unsupervised, have been developed and even recent techniques fit into these categories (Cihlar, 2000). For general mapping of Canada's landmass, unsupervised classification has been the tool of choice (Cihlar et al., 1998) because of the (poorly understood or unknown) diversity of spectral properties of land cover. Its greatest advantage is the opportunity to fully exploit the information content of satellite data, regardless of the geographic area or its surface characteristics, provided that the analyst has the knowledge required for labeling. From a detailed initial land cover map other products may be derived for specific purposes, e.g. for biodiversity modeling. Thus, unsupervised approaches have been preferred in large area mapping applications involving Landsat data (Cihlar, 2000).

In addition to the labeling that relies on analyst's expertise, exploratory research has been carried out on model-based labeling (Peddle et al., 2001). The main potential advantages of this method are reduced cost and increased efficiency of the classification process and a more effective way of dealing with phenological differences in the input data. The initial encouraging results suggest that with further research this approach may be a viable alternative to the analyst-based procedure; for this reason it is also briefly discussed below.

2.4.1 Initial clustering: a hybrid procedure

Classification is a process of generalization, where the initial entities are grouped into a small set of categories. Since the initial number of spectrally unique pixels is very high, a part of the clustering process may be carried out without losing any land cover type information. In Canada, procedures have been developed over the last several years that combine the strengths of computer processing and visual interpretation/analyst expertise (Cihlar et al., 1998; Beaubien et al., 1999; Latifovic et al., 1999; Cihlar et al., 2000). In a combined form briefly described below they have been used successfully to produce detailed land cover maps from TM data (Cihlar et al., 2002). While applicable to multidate data sources, the procedures focus on making maximum use of the spectral information from single-date images.

The hybrid procedure (Figure 3) grew out of research in two classification techniques. Enhancement Classification Method (ECM; Beaubien et al., 1999) is based on years of experimenting with Landsat image enhancements (Beaubien, 1984, 1986, 1994). Its principal characteristic is the retention of most of the land cover type information present in the satellite data, so that when the classified image is visually compared with the original data (contrast-stretched using a formalised set of steps), the observer finds minimal (and justified) difference between the two. Each generalization step is quality controlled through a visual comparison with an enhanced original image, and any unacceptable generalizations are reversed. ECM requires considerable expertise by the analyst that is not easily learned. In contrast, Classification by Progressive Generalization (CPG; Cihlar et al., 1998) was developed to standardise and automate as many as possible of the classification steps, and to use spatial distribution as an additional clustering criterion. CPG divides the procedure into two parts: automated computer processing, and interactive labelling. The automated processing consists of two phases. In the first phase the algorithm divides the multidimensional spectral space into a number (~8000 for a typical boreal scene) of spectrally very similar pixel groups. In the second phase it combines clusters using spectral similarity and spatial adjacency criteria until there are sufficiently few clusters (<~70) for labelling. The two CPG phases are independent, thus allowing combinations with other methodological approaches.

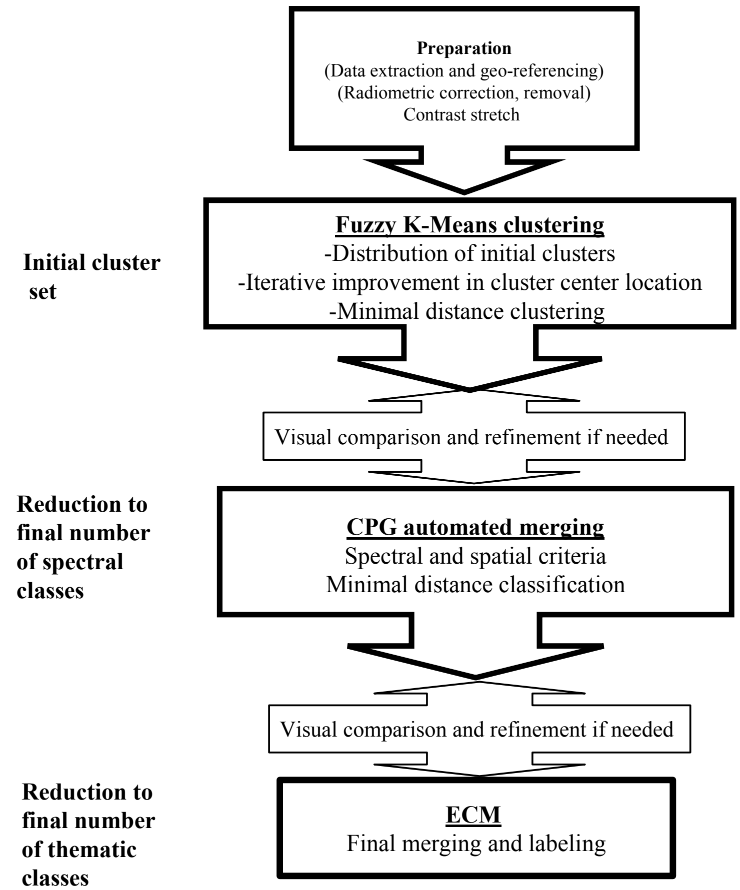

Figure 3. Flowchart for the hybrid classification method

In applying CPG, it was found that its performance could not consistently achieve the level of detail provided by ECM. Although significant improvements were obtained in the automated processing stream through constraining the clustering process by cluster size (Latifovic et al., 1999; Cihlar et al., 2000), it was determined that the high level of detail and consistency of ECM requires more substantive analyst involvement. It was also found (Cihlar et al., 2000) that a) the K-Means algorithm achieves results similar to the initial part of CPG, in addition to being easier to apply since it is part of commercial image software packages; and b) best results (i.e., most spectrally homogenous and spatially cohesive clusters) were obtained by combining fuzzy K-Means with CPG.

The main decision rule for cluster merging in CPG is given by E. 1x (Latifovic et al., 1999):

If ($N_{current} > N_{cl,end}$) and ($NP_i < NP_l$) and ($NP_j < NP_l$) and ($SD_{ij} \leq SD_{max}$) then merge. [3]

where $N_{current}$ is the current number of clusters; $N_{cl,end}$ is the number of desired clusters (determined from SD_{ij} table and SD_{max} value); NP_i, NP_j are the sizes of clusters *i* and *j*; SD_{max} is the maximum allowable *SD* for *i*, *j* to merge (Eq. 2x); NP_l is threshold cluster size to consider a cluster for merging (Eq. 3); SD_{ij} is the spectral distance of centroids of clusters *i and j* (Eq. 4x):

$$SD_{\max} = \sqrt{\sum q_k^{\ 2}} \ , \qquad [4]$$

$$NP_l = NP_a * \frac{N_{cl,st}}{N_{cl,end}} \ , \qquad [5]$$

$$SD_{i,j} = \sqrt{\sum_{k=1}^{N_k} \left(C_{i,k} - C_{j,k}\right)^2} \ , \qquad [6]$$

where:

q_k is number of digital levels per quantised level in the k^{th} spectral dimension (Cihlar *et al.,* 1998);

NP_a is the average cluster size in the input classified image (prior to cluster merging);

$N_{cl,st}$ is the number of clusters in the input classified image;

$C_{i,k}$ is the mean cluster DN value for spectral band *k* of cluster *i*, $i \neq j$;

N_k is the number of spectral bands.

A combined approach presented below thus employs the most effective (in terms of accuracy and time/cost) features of all three procedures. The flowchart is shown in Figure 3. In practice, the initial number of clusters of 150 has been found sufficient, and a nominal seeding of initial clusters is used (Cihlar et al. (2000) employed PCI implementation of fuzzy K-Means described by Bezdek, 1973). CPG then merges clusters that are spectrally similar and spatially adjacent, using fixed or user-defined merging thresholds (refer to Latifovic et al. (1996) and Cihlar et al. (2000) for details). The ECM approach is used to check that no information was lost at each major stage (Figure 3), and to reintroduce omissions due to excessive clustering into the data to be classified (in effect breaking up clusters).

2.4.2 Labeling by analyst

ECM is used in merging clusters and labelling, again in two steps. The initial merging is done without assigning definitive labels and by using within-image information only (i.e., photo interpretation-like approach). This further reduces the number of distinct clusters, typically to ~40-50. In the final labelling, knowledge of the area is most important since it permits the analyst to assign labels with limited ground data. Detailed air photos or comparable data are very helpful at this stage. The corrupted pixels (clouds, strong haze, etc.) are also dealt with at this stage.

It should be noted that this combined classification procedure yields very detailed maps, by capturing all land cover information discernible on the original enhanced images in a controlled way. Where such level of detail is not required, the analyst's time will be reduced (for checking intermediate steps and for labeling) and the procedure will be speeded up accordingly.

2.4.3 Labeling through modeling

A different approach to cluster labeling involves use of geometric optical reflectance models which provide direct associations between satellite image digital numbers and species-specific vegetation structure. These computer-based models provide a 3-dimensional mathematical representation of the natural environment as viewed by a remote sensing instrument (Li and Strahler, 1985). The Earth's surface is modeled in terms of plant canopy structure (height, width, shape), plant distribution (density, spatial arrangement), understory or ground characteristics (i.e. what is visible between plant canopies – typically ground vegetation, secondary understory vegetation, soil, or snow), and shadows. The full sun-sensor-surface geometry that exists at the time of satellite image acquisition is also specified in the model. The required model inputs in forward mode describe plant canopy structure and distribution, from which the model computes reflectance values over specified wavelengths.

The MFM-5 Scale model-based labeling approach now under development is shown in Figure 4. A critical step was the development of the Multiple-Forward-Mode (MFM) strategy (Peddle, 1999; Peddle et al., 2002a,b) to circumvent the need for direct model inversion. MFM obtains a series of forward-mode runs of a reflectance model to generate a Look-up Table (MFM-LUT). MFM-LUT contains a range of input combinations of vegetation structural parameters and the corresponding spectral reflectance for each combination. An improved reflectance model (5-Scale; Leblanc and Chen, 2000) was chosen for use in the boreal environment (Cihlar et al., 1999). The required model inputs are component spectra (leaves, understory, etc., which are available from field measurements, modeling, or spectral libraries), ranges of

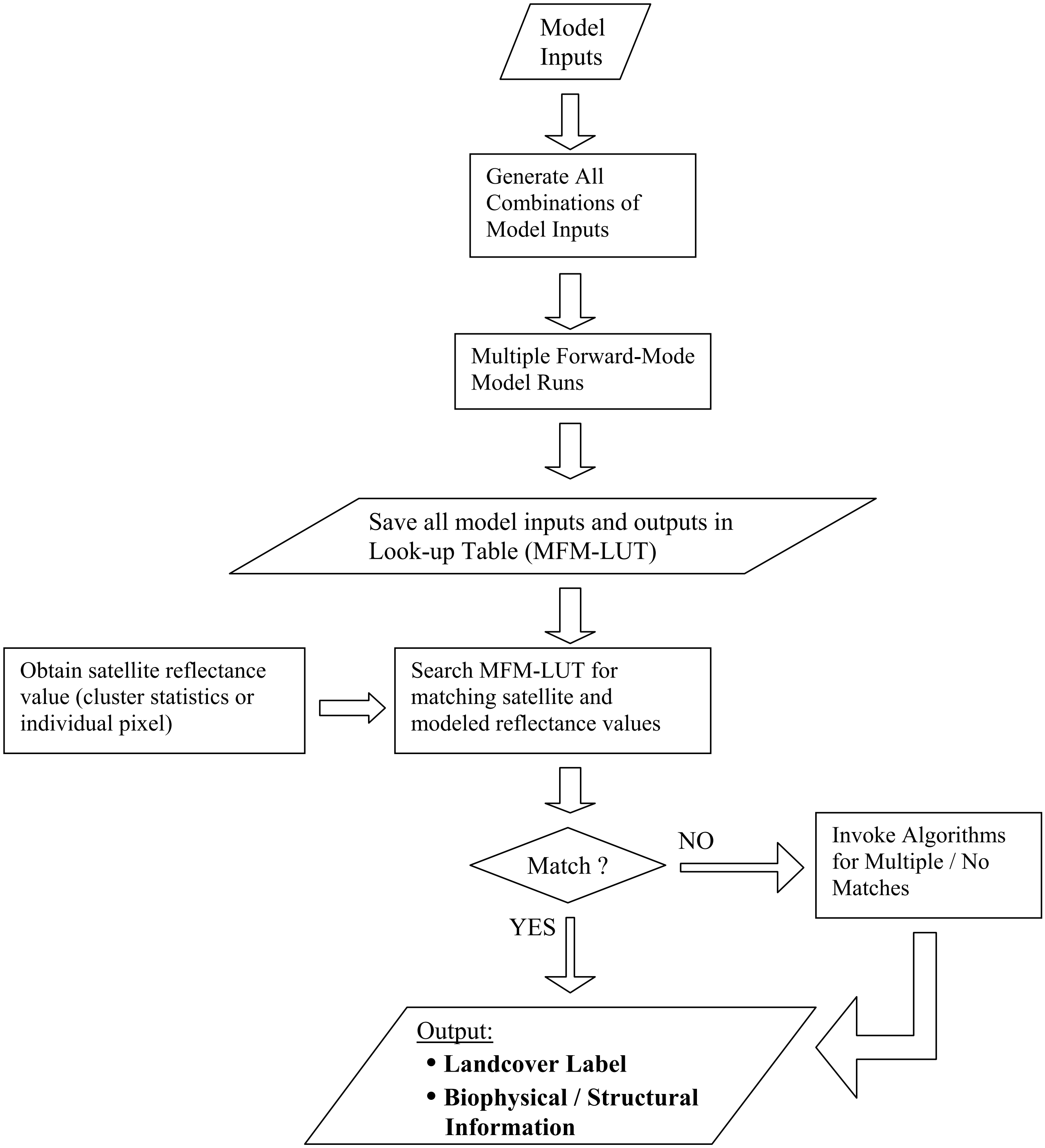

Figure 4. Flowchart for the MFM-5-Scale method

vegetation structural parameters (specified as minimum and maximum values – exact values not required), and image acquisition date, time and view angle. Topographic information (slope, aspect) can also be specified. In labeling, MFM-LUT is searched for matches between actual satellite image values and the modeled reflectance values. It is possible to label clusters or individual pixels. The identified matches provide a land cover class label and also a set of structural descriptors suitable for biophysical parameter estimation (direct or derived). Algorithms have been developed to resolve ties among multiple matches, and also for model parameter retrieval if no exact matches are found (Peddle et al., 2002a). MFM has also been applied successfully to the derivation of forest structure in a change detection study in New Brunswick (Peddle et al., 2002b), and a series of tests in montane forests of the Canadian Rockies, in which a model- based terrain normalisation component has been incorporated into MFM for use in mountainous regions (Johnson et al., 2000).

MFM-5-Scale was initially used to label forest clusters produced using the CPG method (Cihlar et al., 1998). Three sets of hierarchical classes were processed for the BOREAS southern modeling sub-area (Landsat TM path 36/row 22) containing conifer/deciduous classes with and without four density sub-classes, as well as a 12-class set of species specific and density classes. MFM-5-Scale results were compared with a standard maximum likelihood (ML) classification product, and validated against an independently produced land cover map from a provincial forest inventory for deriving classification accuracies over a large sample area (Peddle et al., 2002a). MFM-5-Scale cluster-labeling results were consistent over all three hierarchical levels, and slightly higher than ML for the most general classes (87% vs. 82%), but were 10% lower for the most detailed set of 12 classes (71% vs. 61%)%), while the individual per-pixel MFM-5-Scale accuracy was equivalent or higher than the ML and MFM cluster labeled accuracies in all tests.

MFM-5-Scale was subsequently applied to the BOREAS Region and more complex classes, and compared to a BOREAS land cover classification in Figure 5 as well as to field data. Comparisons were done separately for 12 forestry classes and for all (28) land cover types. Field validation from 136 BOREAS sites indicated an overall classification accuracy for the 12 forest classes of 91% for ECM and 85% for MFM-5-Scale. Over a much larger sample (6000 randomly selected pixels), the two classifications showed 76% agreement (Peddle et al., 2001). A separate test involving low, medium and high density coniferous and deciduous classes showed 94% agreement between the MFM-5-Scale and ECM products (n=3730). In the accuracy comparison for 28 classes (12 forest species and density, 4 mixed forest, 3 agricultural, and a variety of others - grassland, shrub, burns, etc.), the MFM-5-Scale and ECM agreed in 76% for a random sample of 13,046 pixels (Peddle et al., 2002c).

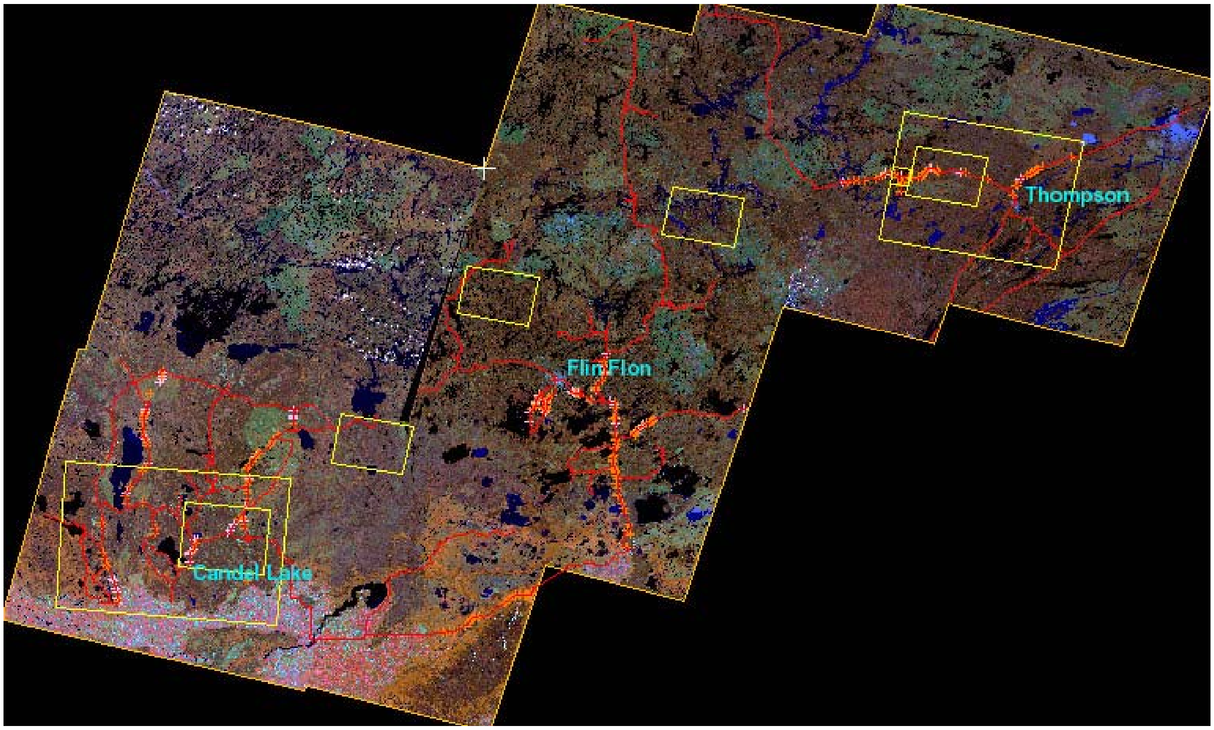

Figure 5. Application of the procedures described to land cover mapping of the BOREAS transect. From Beaubien et al. (2001).

Based on experience to date, MFM-5-Scale represents a potentially attractive alternative to the more subjective land cover classification approaches. The main advantages of the model-based labeling are its potential for automation in using data from different years or seasons and at regional to continental scales; the capacity to provide both land cover classification and biophysical-structural information (e.g. LAI, biomass, productivity) in an objective and repeatable format with minimal or no subjective user intervention; easy use of different class structures, hierarchical stratification, cluster labeling or stand-alone products; and provision of sub-pixel scale information for follow-on analyses. An important potential advantage is reusability of the LUT and its easy augmentation for new conditions, in effect providing a 'permanent training data set'. Although this approach to date has been demonstrated to show potential, it still requires further development and testing that should focus particularly on (i) further analysis of multi-image, multi-date spectral inputs, (ii) testing in other forested areas in Canada (including those with significant topography), and (iii) further development for application to non-forested areas.

2.5 Accuracy and confidence assessment

The use of other remote sensing data in combination with field observations is a typical approach to assessing accuracy of land cover maps (see Cihlar, 2000 for review). The sampling sites are selected with some sampling strategy and used to compare 'classified' results with 'truth'. Confusion matrices are the basic means from which accuracy assessment measures are derived. This approach, although important, has several limitations. First, it is expensive and therefore only a very small fraction of the product pixels can be realistically checked in this way. Second, a single confusion matrix will typically be generated and used to characterize large geographic regions that in themselves may exhibit significant variations in class mixes and hence user accuracies (e.g., Cihlar et al. 2002). Finally, confusion matrix analysis is a generic approach which models accuracy at the class level, and therefore does not account for accuracy implications associated with the classification methodology. These factors do not preclude the need for an accuracy assessment but they imply the need for complementary approaches.

At northern latitudes, Landsat orbits overlap significantly from approximately 40% at the southern border to >80% in Canada's Arctic (Wulder and Seemann, 2000). The overlapping images may be employed in classifying the same area, and the results used to assess the quality of the land cover map (Guindon and Edmonds, 2001, 2002). If entire scenes are classified (as opposed to a non-overlapping mosaic), adjacent scenes provide independent classifications and their levels of classification consistency can be used as an indicator of classification quality.

'Confidence' can be quantified using the following simple example. Suppose overlapping classifications are available from scenes 1 and 2 and that in scene 1 there exists a cluster that has been labelled as A. The consistency of this cluster is defined as the fraction of pixels in the overlap region of the cluster in question that is also labelled as A in scene 2. In the case of cluster-based labeling, consistency and confidence can be assessed at the cluster level and interpreted as a confidence surrogate, thereby providing a more detailed description of relative accuracy than is currently available from conventional confusion matrices. These confidence measures can then be applied at the pixel level to generate a 'confidence' overlay for the land cover product (Guindon and Edmonds, 2001, 2002).

It should be noted that land cover mapping based on regional image mosaics does not preclude exploiting overlap consistency. Although redundant coverage has been eliminated in the mosaic, consistency analyses can still be undertaken by retroactively classifying the full input scenes.

3. Example and implications

Figure 5 shows a land cover classification obtained using algorithms described in this paper, with the exception of HOT and the confidence assessment based on overlapping areas. The area covered by 7 Landsat TM scenes includes the BOREAS transect in central Saskatchewan and Manitoba, and contains typical boreal land cover types. Thirty different categories were mapped in this area. Using field observations, the accuracy of this classification was determined to be 90.7% (Beaubien et al., 2001). These results, obtained by classifying the entire mosaic in one step, confirm the soundness of the overall procedure.

Discussion in previous sections shows that a distinction can be made between 'preprocessing' operations which may be carried out mostly in automated mode (with adequate quality control) and 'labeling' which is a classification legend- specific, analyst- intensive procedure. This approach also enables dealing with a diversity of information requirements and potentially incompatible mapping legends, provided that no useful land cover information is lost at the preprocessing stage. In addition, it is evident that the relative roles of automated and analyst-driven approaches can be modified depending on the required number of classes (and their accuracy).

For the preprocessing phase, we have described a set of algorithms which yield an intermediate image product of high quality. The algorithms were all implemented in research mode, and in some cases (hybrid clustering, consistency analysis in overlapping regions) for volume processing. In addition, a system was developed to handle large numbers (tens to hundreds) of Landsat scenes for classification (Guindon, 2002). Thus, although some further algorithm development and coding is needed, the stage is nearly set for large-scale processing leading to land cover classification product(s).

More attention is needed to the transformation of spectral clusters into land cover maps and their validation. This presumes that (i) the product requirements have been defined and the classification legend has been selected; (ii) the practical problems associated with labeling have been addressed, especially ways of dealing with spectrally ambiguous/nonspecific or locally corrupted data (clouds, haze); and (iii) accuracy assessment procedures have been addressed and funded. The broader the intended audience for this product, the more time and effort will be required to resolve these issues. However, initial answers to these issues may be given based on work to date.

(i) **Classification legend.** From the national perspective it is essential that the result of the mapping be a country-wide consistent land cover product. This requires the choice of a classification legend that meets most present or anticipated requirements. This may be a difficult choice since about 50 different classification schemes have been used (Richardson et al., 2001). In the project Satellite Information for the Landcover of Canada (SILC; Cihlar et al., 2001), we have successfully employed the National Vegetation Classification System (NVCS; FGDC, 1997; Grossman et al., 1998) proposed by the U.S. Federal Geographic Data Committee (FGDC) as an international standard. NVCS is a hierarchical scheme mostly based on vegetation characteristics, but at the most detailed levels it differentiates among species associations. In SILC, we have used its flexibility to retain some detailed classes that may be discerned in spectral satellite data, and to combine classes mapped with coarse or fine resolution data into one consistent scheme (Cihlar et al., 2002). NVCS has also been examined by other Canadian agencies (e.g., Baldwin, 2000; Ponomarenko and Alvo, 2001) and its overall suitability for Canadian conditions has been assessed. Among added advantages of NVCS are its official status and widespread use in the US, thus facilitating consistent continental applications; and compatibility with other international schemes, notably that of UNESCO from which it originated (UNESCO, 1973) and FAO (Di Gregorio and Jansen, 2000).

Although a single classification such as NVCS may encompass the range of land cover conditions, in Canada, it does not automatically follow that such a legend will meet all the user needs. Forest land is an example. In Canada, forest stewardship rests largely with the provinces and their requirements must therefore be considered. The Canadian Council of Forest Ministers, in conjunction with the National Forest Inventory (NFI) of the Canadian Forest Service have adopted a vegetation resources inventory appropriate for Canada's forests, with an accompanying classification legend (Wulder and Nelson, 2001). Similarly, FCCC reporting requires information on three precisely defined cover types (IPCC, 1999). The overall classification approach described here (Figure 1) offers two potential solutions to this dilemma, (i) a combined classification legend and (ii) separate labeling streams. Regarding (i), from the above discussion it may be concluded that NVCS is a suitable classification legend for a Landsat-based land cover map of Canada. Because of its flexibility and hierarchical nature, it may be amenable to changes which will satisfy the needs of all major product users. This could be accomplished by (a) establishing correspondence between classes from different classification legends or (b) by adding new categories to NVCS. The second option is to be preferred since it avoids the potentially difficult problem of mismatches between class thresholds in the different classification schemes.

Where approach (i) does not lead to resolution, solution (ii) may be used to provide unlimited flexibility in the choice of classification legend. The difference between (i) and (ii) is basically a trade-off between the mapping costs (from added labeling streams, accuracy assessment, and product support) and benefits (from a more optimized classification legend). If different legends are used but each within a certain region/biome, there is an additional issue of the compatibility of these within the national framework. In other words, the different legends would need to be consistent at a level of generalization that meets the needs of users interested in data across the entire landmass. In any case, these complexities imply that the suitability of the NVCS (or its modification) for the intended thematic applications should be assessed, and the feasibility of its adjustment evaluated. The fact that NVCS describes basic vegetation characteristics lends some confidence that option (i) will work but in any case, exploratory studies are necessary.

(ii) **Labeling issues.** In terms of impact, labeling is one of the key steps affecting the accuracy of the final product. Experience in SILC and in large US mapping projects (e.g., Vogelmann et al., 2001b) indicates that a significant portion of the spectral clusters may be labeled on the basis of their image appearance, provided that the analyst has the necessary training and practical knowledge of the region under consideration. However, there are also important classes with overlapping clusters which cannot be satisfactorily differentiated within single-date satellite images. They include urban areas, some wetlands, and some crop types. Such confusions are usually resolved through a combination of multi-date images, ancillary information, increased amount of field data, or relaxed information requirements (e.g., fewer thematic categories). The degree of confusion is difficult to determine *a priori* as it may also depend on the acquisition date and the geographic area of interest. The solutions are thus developed on an ad-hoc basis as the specific problems emerge. An intrinsic limitation in Canada is the lack of detailed ancillary data sets, e.g. for wetlands.

Highly dynamic areas such as agricultural regions present a particular challenge since inter-scene radiometric consistency can be affected by crop rotation and growth practices. While a qualitatively (i.e., visually) satisfactory image mosaic can be achieved, seasonal differences may nevertheless be present. This can be dealt with in the labeling process, by partitioning the mosaic into segments and labeling the temporally dynamic clusters separately within each segment.

Additional research is needed on the model- based labeling. The work so far indicates good success in forests, but other cover types offer significant challenges. For example, boreal wetlands are spectrally highly heterogeneous, as are urban and agricultural areas. This may be dealt with directly by associating LUT entries with observed reflectances, or indirectly by first estimating biophysical parameters (e.g., leaf area, fraction of ground cover) and then constructing a classification legend suited to the application (e.g., GOFC Design Team, 1999).

(iii) **Accuracy assessment.** A quantitative confidence assessment based on overlapping areas should clearly be a fundamental component of accuracy assessment, and should be included as a separate layer with pixel- specific content. Classification consistency as quantified above can serve as suitable surrogate measure of accuracy. Beyond that, the amount of available resources and the consequences of map errors will dictate the approach among the existing techniques to be used (e.g., Congalton, 1991, 1996). Since the amount of resources and consequences of map errors are also related, resolution of these issues requires involvement of the product users.

4. Summary

A nationally consistent map portraying the distribution of land cover with a fairly high spatial resolution (~30 m) is a relatively recent but urgent requirement for various scientific, policy and reporting purposes. We have identified five such areas but others will emerge as the product is developed and becomes available. At the present time, the high cost of completing such a product is the main impediment.

Based on research carried out at the Canada Centre for Remote Sensing and the Canadian Forest Service over the last five years, we describe a methodology that will make optimum use of satellite data, be responsive to differences in user needs, and minimize the costs of the mapping program at the national scale. It divides the task into two phases, computer processing (which can be largely automated) and labeling followed by accuracy assessment (an analyst- intensive operation with appropriate computer support). The innovative features of the methodology are haze identification and correction, radiometric normalization over large areas, optimized spectral clustering, quantitative confidence assessment based on image overlaps, and judicious involvement of the analyst at key stages of the computer processing. Most of the innovations were used in preparing a regional mosaic over the BOREAS study area (Figure 5) which was shown to be an accurate land cover product. We also describe a model- based classification scheme under development that has several significant advantages over the traditional, analyst's based labeling and offers a promise for large area applications within a few years.

Besides identifying financial and human resources required to carry out such a national mapping program, an issue concerned with mapping legends remains to be addressed. Specifically, comparative tests and assessment are required to determine if the NVCS-based mapping legend can accommodate the different needs or, alternatively, if different legends are necessary and the approach to ensuring national consistency. These tests require collaboration among scientists representing the various user communities and should be conducted as a matter of priority. Since the question of compatibility of classification legends and map products is a generic mapping issue, results of these tests may be relevant beyond land cover.

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