Preprint/Prétirage

LAND COVER MAPPING OF LARGE AREAS FROM SATELLITES: STATUS AND RESEARCH PRIORITIES

Josef Cihlar
Canada Centre for Remote Sensing
Ottawa, Canada
K1A 0Y7
josef.cihlar@ccrs.nrcan.gc.ca

ABSTRACT

Although land cover mapping is one of the earliest applications of remote sensing technology, routine mapping over large areas has been under consideration only relatively recently. This change has resulted from new information requirements as well as from new developments in remote sensing science and technology. In the near future, new data types will become available that will enable marked progress to be made in land cover mapping over large areas at a range of spatial resolutions. This paper is concerned with land cover mapping strategies based on 'coarse' and 'fine' resolution satellite data as well as their combinations. The status of land cover mapping is discussed in relation to requirements, data sources, and analysis methodologies including pixel or scene compositing, radiometric corrections, classification, and accuracy assessment. The overview sets the stage for identifying research priorities in data preprocessing and classification in relation to the forthcoming improvements in data sources as well as new requirements for land cover information.

1. INTRODUCTION AND OBJECTIVE

Land cover, i.e. the composition and characteristics of the land surface elements, is key environmental information. It is important for many scientific, resource management, and policy purposes and for a range of human activities. It is an important determinant of land use and thus of value of land to the society. Land cover varies at a range of spatial scales from local to global, and at temporal frequencies of days to millennia. As the need for environmental planning and management became important, an accompanying call for land cover information emerged in parallel.

Land cover mapping is a product of the development of remote sensing, initially through aerial photography (Colwell, 1960). This is because 'viewing' large areas repeatedly is necessary for acquiring information about land cover. For the same reason, land cover mapping has been perhaps the most widely studied problem employing satellite data, beginning with Landsat 1. However, most of the studies using 'fine' resolution data (i.e., <~50-100 m) were methodological in nature, exploring various information extraction techniques and applying these over limited areas. Applications over large areas were hampered by the lack of suitable technology, an absence of a user community with a strong need for such information, a lack of appropriate analysis methodologies, and the cost of data. Thus, at the global level, land cover data sets compiled from ground surveys or various national sources (Mathews, 1983; Olson et al., 1983) were for a number of years the major source of information.

Partly in view of the above obstacles (data volume, cost,..), since the late 1980s an increased attention has been given to the use of coarse resolution optical data, represented primarily by NOAA Advanced Very High Resolution Radiometer (AVHRR) images. These were initially available at the 8 km resolution and later, through the initiative of the International Geosphere-Biosphere Programme (IGBP; Townshend et al., 1994) and a project involving many AVHRR receiving stations (Eidenshink and Faundeen, 1994), at the nominal resolution of 1 km for all land areas of the globe. Through these efforts, first satellite-based global land cover maps have already been produced (DeFries and Townshend, 1994; DeFries et al., 1998; Loveland et al., 1999; Hansen et al., 1998).

For coarse as well as fine resolution data, the above limiting factors are changing at the present time. The emergence of global environmental issues addressed by IGBP(1990), the Framework Convention for Climate Change, the Kyoto Protocol, the Biodiversity Convention, global observing systems (GCOS, 1997) and other international policy instruments have brought with it a new, critical requirement for land cover information at many scales, from landscape to global. Computer speed is no longer an obstacle to processing large volumes of data by a small team. The cost of data has been gradually decreasing (especially data for research purposes), and will change fundamentally with the expected launch of Landsat 7. The launch of new satellite sensors such as Landsat 7 (http://landsat.gsfc.nasa.gov/), SPOT 4 VEGETATION (VGT; Saint, 1992), Moderate Resolution Imaging Spectroradiometer (MODIS; Salomonson et al, 1989; Running et al., 1994; Barnes et al., 1998), Medium Resolution Imaging Spectrometer (MERIS; http://envisat.estec.esa.nl/), and Global Imager (GLI; http://hdsn.eoc.nasda.go.jp/guide/guide/satellite/sendata/gli_e.html) with a systematic global acquisition strategy will inaugurate a new era in land remote sensing, during which (i) high quality data sets will be available globally for land cover mapping applications, and (ii) the remote sensing research community will be expected to deliver sound methodologies for generating land cover information products (as well as the first series of such products).

For the above reasons, the turn of the century is a milestone in land cover mapping, and the future will be unlike the past. It is thus appropriate to take a more detached view of the issues involved, main problem areas, and important research directions for the next several years. This paper focuses on the methodologies for generating land cover information products over large areas. The significance of the methodologies is self-evident, and their impact on the quality of the final products will be decisive. The paper considers the end-to-end process in preparing land cover maps, and the types of algorithms and information extraction procedures. The discussion is limited to land cover mapping, i.e. periodic determination of land cover distribution over the entire area of interest (as opposed to land cover change); and to the use of multispectral optical data, the part of the electromagnetic spectrum found most useful for land cover mapping in research to date.

2. DIMENSIONS OF THE LAND COVER MAPPING PROBLEM

There are several important considerations which determine the characteristics of the resulting land cover information.

1. **Purpose.** Land cover information is obtained for numerous scientific, policy, planning, or management purposes. Within each of these areas, a wide range of needs exists. For example, specific models of vegetation-atmosphere interactions require different types of land cover information (e.g., Sellers et al., 1996, Dickinson et al., 1986). Similarly, productivity models (Liu et al., 1997), hydrological models (Wigmosta et al., 1994), forest inventories (Magnussen, 1997), land use inventories and planning as well as other biophysical resource inventories (Jennings, 1995), and many other activities require land cover information.
2. **Thematic content.** The information may be needed for few cover types (e.g., forest - nonforest); for all cover types and at same (or varying) levels of detail; tailored to specific model requirements; or as continuous variables (e.g., % coniferous forest). The thematic content also has strong effect on the frequency of land cover mapping.
3. **Scale.** Over large areas, land cover information may be required locally (at specific sites, 10^0 -10^3 km^2), at the regional scale (10^4-10^6 km^2), or continental to global scales ($10^{>6}$ km^2).

4. **Data .** The quality of the remote sensing data, and their availability, limit the type and accuracy of the information that may be extracted.
5. **Processing and analysis algorithms.** The characteristics of algorithms employed at the various processing stages are of critical importance, as discussed in more detail below.

The purpose and thematic content help define the classes that must be differentiated in the land cover product, i.e. the mapping legend. Scale, together with the legend, determine the remote sensing data source appropriate to the mapping problem. Data and algorithms employed constrain the information that may be present in the final products. To limit the discussion that follows, it is assumed that the purpose of the land cover mapping is to produce information at regional to global scales (>~10^5 km^2) and for all cover types present (although not necessarily at the same level of thematic detail; e.g., a map could have more detailed classes for forest and less detailed for other types).

Since land cover changes over time the temporal resolution is a critical consideration in choosing the appropriate data type. Figure 1 portrays the relationships between spatial resolution, temporal resolution, and satellite data sources. The broken line identifies the principal domain of interest to large area land cover mapping employing satellite data. Such mapping is not required for very small areas or very frequently (i.e., the lower left part of the graph). Thus, the domain of interest spans the range between two extremes: ‘coarse’ resolution at frequent time intervals (lower right part of the plot), and ‘fine’ resolution at long intervals (upper left). It should be noted that the labels ‘coarse’ and ‘fine’ are relative and that each covers a range of resolutions; for example, ‘coarse’ is appropriate for AVHRR 8 km data but not for MODIS 250 m data. The terms are used in this paper for brevity to categorize a sensor but the qualification must be kept firmly in mind.

The range between the above extremes is a continuum accessible through satellite remote sensing techniques. Theoretically, the entire range could be covered using satellite data from the lower left corner of the range, i.e. data obtained very frequently and at a high spatial resolution. However, this is a practical impossibility at the present, and a cost-ineffective solution at any time because land cover does not change rapidly enough in all places. Thus, a more realistic approach is to consider the range as consisting of discrete components.

Region A (Figure 1) represents mapping with frequently obtained coarse resolution data. With these, it is possible to prepare higher level data sets through pixel compositing procedures (Holben, 1986), thus allowing global land cover maps to be produced at short intervals. In region B, fine resolution data are obtained relatively infrequently. Therefore, given in addition the unavoidable cloud contamination and seasonal phenological effects, data sets suitable for land cover analysis can be compiled only over longer time periods. A coverage of large areas is thus produced through ‘scene compositing’, i.e. by mosaicking the individual images. Region C can utilize land cover products generated by methods in A or B. So far, the approach has been to employ A for mapping and B for training and/or validation (e.g., DeFries et al., 1998; Cihlar and Beaubien, 1998; Hansen et al., 1998). Region D presents the greatest challenge, requiring frequent coverage at fine resolution. While this is not now realistically possible over large areas, it should be feasible to synergistically combine data and products from parts A and B, thus obtaining effectively the same information; this is discussed in more detail in section 3.3. Figure 1 also shows the approximate positions of some important satellite sensors.

So far, satellite-based large area mapping has been mostly done in region A (Figure 1) because of the availability of data and the manageable computational demands. Land cover maps at 8 km resolution or coarser were prepared from AVHRR GAC data (DeFries and Townshend, 1994; DeFries et al., 1998). Maps for landscape regions (e.g., Steayert et al., 1997; Cihlar et al., 1997; Laporte et al., 1998) or larger areas (Loveland et al., 1991, 1995; Cihlar and Beaubien, 1998) have been produced in recent years with 1 km AVHRR data. With the availability of the global AVHRR 1 km data set (Eidenshink and Faundeen, 1994), intensive activities led to global products at the same resolution (Loveland and Belward, 1997; Loveland et al., 1999; Hansen et al., 1998). So far, region A maps have been produced infrequently. However, the same techniques can be used to generate land cover maps at shorter time intervals, as short as the minimum compositing period resulting in a usable data set. - For region B, the work so far has been limited mostly to studies over small areas, such as a Landsat scene or less. Among the exceptions is the US GAP program (Jennings, 1995) through which maps over entire states have been produced (Homer et al., 1997; Driese et al., 1997); humid tropical deforestation studies; and other experimental products prepared through scene compositing (Guindon, 1995; Homer et al., 1997; Beaubien et al., 1998; Vogelmann et al., 1998). Apart from some methodological studies (e.g., Moody and Woodcock, 1996; Cihlar et al., 1998d), little work has been done regarding region D.

3. ANALYSIS METHODS

In principle, land cover mapping from satellite data is straight-forward and consists of four steps: data acquisition, preprocessing, analysis/classification, and product generation and documentation. However, details of these steps differ fundamentally between regions A and B of Figure 1. In A, the acquisition is frequent (every one or very few days), and preprocessing includes image compositing by choosing individual pixels from a period of several days, typically 5-10. Consequently, one can obtain a nominally cloud-free product for every compositing period but at the cost of increased image noise. In part B, images are obtained so infrequently (e.g., >2 weeks) that the pixel compositing approach is not viable and scene compositing must be employed instead. These differences have a strong impact on the preprocessing and classification techniques.

3.1 Preprocessing

The objective of this step is to prepare the data in a format from which accurate land cover information can be extracted. In principle, it entails geometric and radiometric corrections (Figure 2). Geometric corrections will not be discussed here as they have been worked out for both coarse (e.g., Emery et al., 1989; Cracknell and Paithoonwattanakij, 1989; Roberston et al., 1992; Nishihama et al., 1997) and fine (Friedmann, 1981) resolution satellite data.

3.1.1 Coarse resolution data

In the past, some classification projects employing coarse resolution data were carried out with single-date, relatively cloud-free images (e.g., Pokrant, 1991; Beaubien and Simard, 1993). However, this approach is fundamentally limited because the probability of cloud-free scenes decreases as the area covered by one scene increases. It is thus very difficult to obtain useful images for land cover mapping, especially if the eligible time interval is short. Furthermore, such images contain systematic errors due to atmospheric effects (as a function of the path length) as well as monotonically changing spatial resolution for most coarse resolution sensors. Their classification is therefore difficult and requires interactive fine-tuning for each input scene used, as well as post-classification operations to reconcile differences between adjacent scenes and thus ensure consistency across the mapped area. For these reasons, research in recent years emphasized the use of image composites.

In a compositing process, the image product is prepared so as to contain, as much as possible, information about the land surface itself. Since a large fraction of the pixels typically contains clouds, the main objective of the procedure is to select the most cloud-free measurement from those available for a given pixel of the composite image. At the present, the selection is most often based on the maximum value of the Normalized Difference Vegetation Index (NDVI; Holben, 1986). Advantages of the NDVI criterion include high sensitivity to atmospheric contamination, ease of computation and wide acceptance in previous studies, thus creating a *de facto* standard. Others have shown that maximum NDVI composites contain artefacts caused by the behaviour of the NDVI itself (e.g., Goward et al., 1991; Cihlar et. al., 1994a,b; Qi and Kerr, 1994). Nevertheless, the alternatives proposed so far have their own disadvantages; and furthermore, the main drawback, i.e. a tendency to select pixels with forward-scattering geometry, can be overcome through bidirectional reflectance corrections (e.g., Li et al., 1996; Cihlar et al., 1997b; Leroy, 1994; Ba et al., 1997). This is not to say that the compositing problem has been solved (section 4.1).

The pixel compositing approach yields nominally cloud-free composites every several days, thus providing a potentially large data set for land cover classification. However, in this form the data are far from adequate for such a purpose. This is because the composites have built-in noise from the varying satellite sensing geometry and from residual clouds or variable atmospheric properties (water vapour, aerosols, ozone). These effects are normally present between adjacent composite pixels and can lead to large radiometric differences for the same land cover type, thus causing classification errors. They also have a strong impact on the consistency of satellite data, both within and among years. For example, Cihlar et al. (1998b) found that depending on the measurement of interest (AVHRR channel 1, 2 or NDVI) and land cover type, the most important correction is the removal of contaminated pixels, atmospheric correction, or correction for bidirectional reflectance effects caused by differences in the source-target-sensor geometry. Thus, further preprocessing operations are necessary.

The degree of corrections following compositing varies among investigations. Atmospheric corrections are frequently carried out (e.g., James and Kalluri, 1994; Eidenshink and Faundeen, 1994; Cihlar et al., 1997b), although nominal/climatological values of some critical parameters are typically used or their effect is ignored (e.g., aerosol). While the nominal corrections account for systematic effects such as Rayleigh scattering, they are incapable of discerning pixel-specific atmospheric contamination caused by translucent or small (subpixel) clouds, haze, or snow patches. These effects are difficult to detect because present satellite data have insufficient spectral information (thus limiting cloud detection options based on spectral, pixel-based criteria) and because the use of spatial context is even more limited due to the inherent heterogeneity of land cover (especially with decreasing pixel size). Other possibilities thus need to be pursued (Gutman et al., 1994). Use of the temporal dimension is one option (Viovy et al., 1992; Los et al., 1994; Sellers et al.,1994; Cihlar and Howarth, 1994). Sellers et al. (1994) used the NDVI temporal trajectory to flag contaminated pixels, and Cihlar (1996) extended this approach in CECANT (Cloud Elimination from Composites using Albedo and NDVI Trend). Since the detection is NDVI-based, it can identify the above sources of noise because they tend to decrease the measured NDVI (compared to the ‘expected value’ for that pixel and compositing period). CECANT requires that data for the entire growing season be available so that the NDVI curve can be modelled. However, it is also applicable to new (current year) data provided that comparable full-season data are available for a previous year and some degradation of performance can be traded for timeliness (Cihlar et al., 1998e).

Bidirectional corrections are possible but not frequently implemented so far because of the perceived complexity of the problem. Furthermore, bidirectional corrections require satellite measurements at different viewing geometries with the surface conditions remaining constant to maximize the accuracy of the inversion procedure (e.g., Barnsley et al., 1994). Such measurements are generally not available, and this approach may become practically feasible only after the launch of EOS when the bidirectional space is sampled simultaneously by MODIS and MISR (Martonchik et al., 1998). As another option, it is possible to correct satellite data to a standard viewing geometry (Gutman, 1994; Sellers et al., 1994). This option requires the knowledge of which model to apply to each pixel to be corrected. Typically, the models are derived for individual cover types, and land cover thus becomes a pre-requisite to using this approach. The procedure might become somewhat circular, except that the bidirectional dependence does not appear highly cover type-specific and few types need to be differentiated (Wu et al., 1995). Furthermore, the coefficients for these functions need not be known a priori but may be derived from the data set itself (Cihlar et al., 1997b; Chen and Cihlar, 1997). This means that a simple land cover classification (e.g., an existing one or one based on NDVI only which is less sensitive to bidirectional effects) can be used in the correction of satellite data, the latter to be used for a more detailed differentiation of the various cover types or conditions.

3.1.2 Fine resolution data

In the past, most land cover studies employing high resolution data were carried out with single images (hereafter called 'scenes'), parts of scenes, or an assembly of such scenes from different areas. In these cases, radiometric consistency was not an issue because the classification could be optimized individually for each scene. When classifying a scene composite (i.e., mosaic of scenes), the situation is more complicated. In principle, two options are possible (Figure 2). First (case I), one can classify each scene separately and subsequently reconcile the classes across the mosaic. Another approach (case II) is to assemble a mosaic of scenes for the entire area, establish radiometric uniformity across the mosaic, and then classify it as one entity.

In case I, each scene is treated as a separate data set to be classified, using ancillary data that are appropriate for the classification procedure employed. It is thus slow and labour-intensive. The reconciliation of classification across the boundaries between adjacent scenes can be difficult and may require changes in the classification(s) or labeling to be carried out within individual scenes. Even with these measures, discontinuities between scenes are not necessarily removed if significant radiometric differences were present at the outset. Thus, even with much intervention by the analyst, post-classification reconciliation does not guarantee success. On the other hand, procedure I is highly flexible and can cope with various limitations of the input data. It has thus been used extensively in the past and good results have been reported (Pokrant, 1991; Driese et al., 1997).

Because of the infrequent satellite revisits, the compositing of fine resolution data over large areas (case II) employs entire scenes, as opposed to individual pixels in the coarse resolution data. Thus, although radiometric noise is still present, it takes on different forms. First, atmospheric contamination is less limiting because only mostly cloud- and haze-free scenes (preferably <10%) are used for this purpose. Second, bidirectional problems are much less severe, particularly in the case of nadir-looking sensors with a narrow field of view such as the Landsat Thematic Mapper or SPOT HRV in nadir mode. Solar zenith angle corrections are thus the main ones to consider.

Substantial amount of research has been carried out in the area of radiometric equalization across scene composites. Typically, the algorithms utilize overlaps between adjacent scenes to establish the correction factors. The corrections have been done interactively (e.g., Beaubien et al., 1998) or can be automated (Chavez, 1988, 1989; Schott et al., 1988; Elvidge et al., 1995; Yuan and Elvidge, 1996; Atzberger, 1996; Guindon, 1997). However, reconciling adjacent scenes may not be sufficient in larger scene composites. This is because the residual errors accumulate in a different manner, depending on the order of scenes to be corrected (Guindon, 1997). Also, the sequence of corrections is not likely to achieve closure if done unidirectionally, i.e. radiometric values for one cover type may differ between the first and the last scene included in the composite. Therefore, an overall adjustment within the scene composite is preferable, in which the inconsistencies and radiometric differences are balanced to an overall optimum. This is conceptually similar to block adjustment employed in photogrammetry, and can be implemented for scene compositing purposes (e.g., PCI, 1998; Guindon, 1995). With such adjustments, the radiometric errors are minimized across the composite, based on the magnitude of the differences detected in the overlapping areas. These differences can conveniently be detected using overlaps with adjacent scenes or orbits. Because of the scale relationships between scene size and the size of atmospheric high pressure areas, adjacent scenes along the orbit often have similar cloud contamination.

Even in radiometrically corrected scene composites, some noise will remain. The most important sources are local atmospheric effects such as haze, smoke, or cumulus clouds in an otherwise clear-sky scene. Small but potentially significant bidirectional reflectance effects may also be present (Staenz et al., 1984). For example, Guindon (1997) observed differences of 1-5 digital levels between forescatter and backscatter directions in Landsat MSS scenes; such differences could lead to classification discontinuities between adjacent scenes. These residual effects must be dealt with in the classification process.

In addition to purely radiometric noise, the uniformity is also affected by phenological differences among scenes that are more difficult to address. Potential solutions include enlarging the window during which acceptable data are acquired, usually by adding years from which data may be used; using data from other, similar sensors; or attempting a ‘phenological correction’ based on seasonal trajectories established for similar targets. Such corrections would be required prior to scene compositing.

The use of scenes from various sensors in a composite has not been explored so far. In principle, it requires preprocessing the data from the added sensor to resemble the initial one, both spatially and spectrally. Spatial resolution presumes resampling to the same pixel size, a routine operation. Spectral adjustment is conceptually more difficult, and its feasibility will depend on the differences between the two sensors and the spectral characteristics of the targets in the imaged scene. The solution is easiest when the added sensor has more than one spectral band where the initial sensor has only one (e.g., Li and Leighton, 1992). The inverse situation has no satisfactory solution, and may render the added data set unsuitable.

It should be noted that the last two options (phenological correction and compositing scenes from various sensors) will also add radiometric noise of their own. Some form of between-scene reconciliation is therefore likely to be required in many cases. This, and the inevitable residual noise in the scene composite suggest that while case II application may be the preferred solution, in practice it may often have to be supplemented by case I to obtain quality land cover maps.

3.2 Classification

Land cover information that can be gleaned from satellite images are the spectral and spatial attributes of individual cover types. There are some differences between the coarse and fine resolution data, mainly in the relative importance of these two kinds of attributes. Because of the reduced resolution, the spectral dimension is the most important source of cover type information in coarse resolution images. For fine resolution data, the relative importance of the spatial dimension is higher, although the spectral content still dominates in most cases. In the following discussion, no distinction is therefore made between the two data types.

Numerical techniques for satellite image classification have a long tradition, dating back to at least the early 1970s. Two types of approaches have evolved and, in spite of recent developments, have remained as the basic options. They differ in the assumptions made about the knowledge of the scene to be classified. In supervised classification, *a priori* knowledge of all cover types to be mapped within the classified scene is assumed. This knowledge is used to define signatures of the classes of interest, to be applied to the entire scene. In unsupervised classification, no prior information about the land cover types or their distribution is required. Unsupervised classification methods divide the scene into more or less pure spectral clusters, typically constrained by pre-defined parameters characterizing the statistical properties of these clusters and the relationships among adjacent clusters. The assignment of land cover labels to individual spectral clusters is made subsequently on the basis of ground information, obtained in the locations indicated by the resulting clusters. In recent years, numerous variants of these two basic classification methods have been developed. These include decision trees (Hansen et al., 1996); neural networks (Carpenter et al., 1997; Bischof and Leonardins, 1998; Foody et al., 1997; Yool, 1998), fuzzy classification (Foody, 1996, 1998; Mannan et al., 1998), and mixture modeling (van der Meer, 1995) for supervised classification; and classification by progressive generalization (Cihlar et al., 1998a), classification through enhancement (Beaubien et al., 1998), and post-processing adjustments (Lark, 1995a,b) for unsupervised techniques.

It seems evident that when one knows what classes are desired and where they occur (at least as a sample), supervised classification strategies are preferable. However, over large areas the distribution of classes is not known a priori. This is compounded by the spatial trends in spectral signatures, resulting in the well-known signature extension problem. These complexities render sample selection very difficult and often arbitrary. Thus, where spatial distribution information is not available, e.g. when mapping a large area previously not well known, unsupervised classification is arguably the better strategy (e.g., Achard and Estreguil, 1995; Cihlar and Beaubien, 1998), although a supervised method has also been used in such case (Hansen et al., 1998). Unsupervised classification provides a more comprehensive information on the spectral characteristics of the area, presents spectrally pure clusters for the labelling step, and gives the opportunity to the analyst to group similar clusters into a smaller number of land cover classes. Perhaps the major problem with unsupervised classification is the effect of controlled parameters (e.g., number of clusters, allowable dispersion around a cluster mean) as for the same data set, changes in these can produce different final clusters. A recent way of circumventing this limitation has been to produce a large number of clusters, typically 100-400 (Kelly and White, 1993; Driese et al., 1997; Homer et al., 1997; Cihlar and Beaubien, 1998; Cihlar et al., 1998a; Vogelmann et al., 1998). The large number of clusters is then reduced by well-defined merging steps. The merging procedure can be based on statistical measures (i.e., again unsupervised), or can be carried out interactively by the analyst (e.g., Figure 3). Given the large number of clusters in relation to the small number of resulting land cover types, the impact of control parameters on the final product is diminished in this case. - Another important limitation of unsupervised classification is the potential mismatch between spectral clusters and thematic classes. The hyperclustering approach also mitigates this problem but additional steps may be necessary (Lark, 1995b). Independent ground information is required by supervised or unsupervised method. The important advantage of the latter is that the concerns about the location and representativeness of the ground data are much reduced because the clusters are homogenous by definition.

While most classification strategies have focused on the use of the spectral dimension, the spatial domain also contains important information, especially in fine resolution data. Although numerous algorithms have been developed to quantify spatial relations within images such as texture (Gong et al., 1992), segment homogeneity (Kartikeyan et al., 1998 and references therein) and various others, the spatial dimension has not been used effectively in image classification so far. Spatial measures can be employed in supervised or unsupervised classification as additional channels, in unsupervised classification for cluster merging, as a pre-classifying step resulting in homogenous patches (per-field classifiers), and in other ways. Given the contribution that spatial attributes can make to land cover classification, their increased use is most desirable. Recent interest in an effective use of spatial and spectral information (Shimabukuro et al., 1997; Kartikeyan et al., 1998) is therefore encouraging.

An important consideration in land cover classification is consistency and reproducibility. That is, the same result should be obtained by various analysts given the same input data or ideally, even different input data over the same area. In practice, this means that as much as possible of the analysis should be done with objective, analyst-independent procedures. On the other hand, the analyst cannot be entirely excluded from the process because any classification is a human construct, imposing an artificial scheme on the natural world. One way of dealing with this dichotomy is to separate the tasks into distinct phases. For example, Cihlar et al. (1998a) described ‘classification by progressive generalization’, a non-iterative unsupervised classification procedure in which the selection of training samples, classification and initial merging of clusters are automated and thus fully reproducible (Figure 3). In the last stage preceding labelling, the analyst is presented with suggestions for merging the remaining clusters but the decision is his/hers. The suggested merging is based on both spectral and spatial relations between the remaining cluster pairs. In this way, the number of clusters can be reduced to a few dozen (typically 70-120 in boreal ecosystems) without the need for ground information.

3.3 Map frequently and at high spatial resolution?

Region D in Figure 1 represents land cover mapping applications at high spatial resolution and short time intervals. Over large areas, such applications are rare if any, at the present time. High resolution satellite data are routinely employed over large areas, e.g. for annual crop assessment (de Boissezon et al., 1993), but in a sampling mode. The minimum required temporal frequency for land cover mapping at present appears to be about 5 years (Ahern et al., 1998; GCOS, 1997). Nevertheless, it is desirable to know about the changes in land cover composition, though not the location of these changes for policy purposes, to satisfy reporting requirements, to assess the impact of management measures, or for other reasons. Thus, the question arises: can requirements in D be met by a combination of full coarse resolution coverage and a sample of high resolution data? Importantly, such an approach could also meet some of the high resolution coverage (region B in Figure 1) but at a considerably lower cost.

Numerous studies have demonstrated the effectiveness of combining coarse and fine resolution images in estimating the area of one class, e.g. forests (Mayaux and Lambin, 1995, 1997; DeFries et al., 1997; Mayaux et al., 1998). When dealing with many classes, the methodological considerations are more complex (Walsh and Burk, 1993; Moody and Woodcock, 1996). Given a coarse resolution land cover map for an area (domain), it may be used to stratify the domain into units with a similar composition, then sample these with high resolution data. The challenge is in finding appropriate stratification and sampling framework that uses the domain coverage effectively. Cihlar et al. (1998c) proposed a methodology based on a domain coverage by coarse resolution data and a potential sample of high resolution images (full frame), as specified by the path/row grid for high resolution sensors such as Landsat Thematic Mapper (NASA, 1982). With these two inputs, one can determine land cover composition for both the domain and each potential image/sample unit, and thus quantify the similarity between the two. Cihlar et al. (1998c) chose Euclidean distance for composition and contagion index (O'Neill et al., 1988) for fragmentation but various other measures are possible. They then postulated that the optimum sample is one which most closely approximates the composition of the domain land cover. In this scheme, the high resolution sample images are selected, one at a time, on the basis of their ability to bring the composition of the sample close to that of the domain. In testing the effectiveness of this scheme to assess the proportions of land cover types over an 136,432 km^2 area, Cihlar et al. (1998d) found that this selection method converges rapidly on the actual area of individual land classes. The selected sample was 1.5 to 2.1 times more effective in reducing the relative error than a random sample of the same size, allowing to obtain a comparable (higher) precision at a lower (the same) cost. It should be noted that once the composition of the coarse resolution land cover classes is determined in this manner, the approximate spatial distribution of individual classes at fine resolution is also known since it can be expressed as fraction of each coarse resolution pixel; thus, a map for the region D (Figure 1) can also be produced, although it will not have the pixel-specific accuracy at the fine spatial resolution.

3.4 Accuracy assessment

No land cover classification project would be complete without an accuracy assessment. It may well be that concern about the accuracy of land cover maps did not exist before the advent of satellite-based methods and photo interpretation-based maps were assumed 100% accurate (this is still often the case, e.g. in forest inventories). The need for accuracy assessment initially arose as part of algorithm development, and it was extended into an important tool for users of land cover products. Many papers have been written on the methods of accuracy assessment, and various accuracy measures have been defined (e.g., Hord and Brooner, 1976; Thomas and Allcock, 1984; Rosenfield and Fitzpatrick-Lins, 1986; Congalton, 1991; Hammond and Verbyla, 1996; Edwards et al., 1998). At this point, the principles of accuracy assessment are well known. The ideal requirements are based on the sampling theory but practical considerations regarding access, resources, etc. constrain the 'desirable'. There are also methodological difficulties with respect to spatial resolution, mixed pixels in coarse resolution satellite data being of special relevance. At the coarse resolution, many pixels contain a mixture of cover types even in a fairly general classification scheme such as land vs. water, thus creating a difficulty in deciding on the correctness of the assigned label. An obvious approach is to assign the pixel to the single largest cover type within the pixel (e.g., Cihlar et al., 1996; Hansen et al., 1998). This can be accomplished with the aid of fine resolution maps where these are available. However, it is questionable when the dominant land cover type covers much less than 50% of the pixel. Furthermore, since the high resolution maps have errors (as do maps obtained through airborne techniques such as aerial photographs, airborne video, etc.), a definitive accuracy assessment needs to contain 'ground truth' as part of the sampling design (e.g., Magnussen, 1997).

In addition to purely methodological considerations, accuracy assessment tends to be strongly constrained by the resources available. The acquisition of verification data can be expensive, especially if a statistical design is rigorously followed, access is difficult, etc. Within these constraints, however, creative solutions are possible. For example, Kalkhan et al. (1998) described the combined use of air photo interpretation and a sample of ground data to assess the accuracy of Landsat-derived proportions of land cover types, with 200 samples at the first stage and only 25 among these described in the field. To complicate the matters further, ground truth may not necessarily be correct either; its errors can be due to incorrectly specified location, very small land cover patches being used, the inability of the surveyor to see a larger area of the surface, inconsistencies in labeling, etc. Thus, in practice, accuracy assessment is likely to remain a matter of compromise between the ideal and the affordable, or "A balance between what is statistically sound and what is practically attainable must be found..." (Congalton, 1996, p. 124).

4. RESEARCH NEEDS AND OPPORTUNITIES

In general, the needs and opportunities are related to the present and upcoming information requirements over large areas, and the expected evolution in the relevant data and technological tools. In all these areas, land cover mapping applications will receive a strong boost due to: increased demand for information because of concerns about climate change and sustainable development; several new sensors designed with land cover mapping as an important application; and the continuing rapid growth in computing technology.

4.1 Preprocessing

Assuming that the range of land cover mapping requirements is represented by all four areas A-D (Figure 1), the focus needs to be maintained on improving the methods for optimally using data from new coarse and fine resolution sensors. For coarse resolution sensors, this means improved methods for image corrections, especially atmospheric, sensing geometry and pixel contamination. The objective should be to produce a cloud-free composite image which has radiometric properties of a single-date, fixed geometry image obtained during the same period. The availability of high quality, calibrated data from MODIS, MERIS, VGT and GLI will make major improvements possible. This goal cannot be fully achieved for most sensors because of the changing spatial resolution with the viewing angle, although in some cases (e.g., SPOT VGT; Saint, 1992) the resolution is view angle-independent. Innovative ways must be found to define and implement robust, accurate and automated algorithms for the generation of superior composite products. Newly available tools are calibrated data; improved spectral coverage (new as well as sharpened bands); and the considerable progress made in recent years in defining algorithms for atmospheric parameters extraction, bidirectional corrections, etc. Although the ultimate solution is an accurate detection of contaminated pixels and retention of all remaining ones with the associated angular information, compositing will be a necessary preprocessing step for land cover classification in the foreseeable future. Further work on compositing algorithms thus appears warranted, with the currently ubiquitous maximum NDVI criterion used as the basis for comparison.

In the case of fine resolution sensors, the main preprocessing need is for accurate and robust scene compositing. This implies accurate sensor calibration and atmospheric corrections, although these measures alone are not sufficient. Local atmospheric effects (thin clouds, haze, smoke), subtle bidirectional effects, or small phenological changes may yield to algorithmic solutions but they pose a significant challenge. Much more research is needed on the preparation of large-area scene composites, to work out the theoretical and practical problems of dealing with residual atmospheric, phenological and other types of noise. Research is also required on compositing images from different sensors, with the objective of producing mosaics of the same consistency as from one sensor. Once these techniques are developed sufficiently well to be automated, it should be possible to produce 'virtual scene composites', on the basis of which the user could routinely order data set(s) covering the geographic area of interest over the specified compositing period(s). Of course, if any of the above radiometric differences within the composite are not resolved at the preprocessing stage, they must be dealt with during classification.

4.2 Classification

Cihlar et al (1998a) proposed that classification algorithms should ideally satisfy the following requirements: accuracy; reproducibility by others given the same input data; robustness (not sensitive to small changes in the input data); ability to fully exploit the information content of the data; applicability uniformly over the whole domain of interest; and objectiveness (not dependent on the analyst's decisions). Many present digital image classification methods do not meet these criteria, and none meets them completely. Yet, such criteria are fundamental to a scientifically-based methodology. Some of the implications are briefly discussed below.

The interest and innovation in image classification methods has continued in recent years, as has the 'creative tension' between supervised and unsupervised approaches and their variants. This will undoubtedly continue, and it is a healthy and beneficial process which should lead to better algorithms. Work is needed especially in mitigating the limitations of the two basic approaches, supervised and unsupervised, stemming from the fundamental assumptions (Chuvieco and Congalton, 1988; Bauer et al., 1994; Lillesand, 1996).

Although initially digital spectral values were the main input for classification, various types of data have been considered more recently, either during classification (DeFries et al., 1995) or at the labelling stage (Brown et al., 1993). This will be a continuing requirement, especially as the number of spectral bands increases and new bands may prove to carry unique information content (e.g., Eva et al., 1998).

There is a strong need to make better use of spatial information. After all, useful land cover maps were produced from this attribute alone before the advent of colour photography and digital classification. In addition to texture (which is easily computed but not necessarily an informative attribute), more attention needs to be given to other measures such as pattern, shape, and context (Rabben, 1960). Another problem is in optimally and synergistically combining spectral and spatial elements, using one to improve the quantity and quality of land cover information obtained from the other.

A special challenge in image classification is to isolate, and minimize if possible, the role of the analyst in the classification. This is important because reproducibility is a fundamental requirement for any method or product. When the analyst's input is distributed throughout the classification procedure, the result is not reproducible. On the other hand, as long as discrete (thus artificial to some degree) classification legends continue to be used, the analyst's role cannot be eliminated because the class distinctions do not necessarily correspond to equivalent distinctions in reality. However, it is possible to assign a more precise role to the analyst, and to limit his input to specific portions of the classification procedure. This will improve the reproducibility of the entire process, and will highlight the impact of the analyst's decisions. A range of options are possible here. For example, in fuzzy classification approaches, the analyst's role can be reduced to defining the acceptable fractional composition of each class in terms of individual components.

A further step in reducing the subjective component in classifications is to first prepare specific biophysical products with continuous variables. For example, Running et al. (1995) proposed that three variables (permanence of above ground live biomass, leaf area index, leaf longevity) characterize vegetated land cover. If such separate products can be derived from satellite data, individual users can construct an optimized classification legend for all the land cover types or conditions present in the area to meet their specific objective. This does not eliminate need for classifications but renders the whole process more useful because of a better fit of the classification with specific user needs. The challenges here stem from the fact that 'land cover' can imply various characteristics, not all easily translated into biophysical variables that can be derived from satellite data (e.g., the hydrological regime). Nevertheless, this area needs to be pursued because of the potential gains in the utility of satellite-derived information products. The work done so far on two or few classes (e.g., Iverson et al., 1994; Zhu and Evans, 1994; DeFries et al., 1997) needs to be extended to multiple cover types. Data from other sensors, such as satellite radars or lidars (Dubayah et al., 1997) should be useful in developing the fields of continuous variables.

Although for scene composites (Region B, Figure 1) the desirable approach is classifying the entire mosaic as one entity, it is very likely that data limitations will make this impossible in many cases. Local adjustments will thus be needed to achieve optimum results. The locations of these should be evident based on input image quality, but algorithms will be required to make this process reproducible and consistent.

Further research is needed on the synergistic use of data from coarse and fine resolution sensors to span the entire range of requirements represented in Figure 1. Region D is the most demanding, with high spatial and temporal resolutions. It is also an area where large progress can be expected, with the resolution of new sensors around 300 m.

5. CONCLUDING REMARKS

In the last 5-10 years, land cover mapping from satellites has come of age. Although the research on various issues regarding data preprocessing, classification and accuracy assessment has continued, new and unique data land cover products have been generated which could not be produced by earlier techniques. This is only a start, however. Many of the technical limitations hampering further improvements in land cover mapping will be removed in the next few years, especially in the quality of satellite data (improved calibration, spatial and spectral resolution, spectral coverage, geolocation accuracy) and the computing capability, founded on the accumulated knowledge and experience in the use of digital analysis methods. Thus, earth observations have the potential to respond to the growing and urgent demand for timely and accurate land cover information over large areas. The fulfilment of the promise will require strong, ongoing research activities as well as new initiatives in the production of land cover maps. The research agenda needs to address the best ways of taking advantage of the new capabilities and, importantly, the ways of resolving problems identified during the production of the land cover maps.

6. REFERENCES

Achard, F., and C. Estreguil. 1995. Forest classification of southeast Asia using NOAA AVHRR data. Remote Sensing of Environment 54: 198-208.

Ahern, F. J., A. C. Janetos, and E. Langham. 1998. Global Observation of Forest Cover: a CEOS' Integrated Observing Strategy. Proceedings of 27th International Symposium on Remote Sensing of Environment, Tromsø, Norway, June 8-12: 103-105.

Atzberger, C.G. 1996. The spectral correlation concept: an effective new image-based atmospheric correction methodology over land areas. In: Parlow, A. (Ed), Progress in environmental remote sensing research and applications, Balkema, Rotterdam: 125-132.

Ba, M.B., G. Dedieu, Y.H. Kerr, S.E. Nicholson, and J. Lecocq. 1997. Reduction of bidirectional effects in NOAA-AVHRR data acquired during the HAPEX-Sahel experiment. Journal of Hydrology 188-189: 725-748.

Barnes, W.L., T.S. Pagano, and V.V. Salomonson. 1998. Prelaunch characteristics of the Moderate Resolution Imaging Spectrometer (MODIS) on EOS-AM/1. IEEE Transactions on Geoscience and Remote Sensing 36: 1088-1100.

Barnsley, M.J., A.H. Strahler, K.P. Morris, and J-P. Muller. 1994. Sampling the surface bidirectional reflectance distribution function (BRDF): 1. Evaluation of current and future sensors. Remote Sensing Reviews 8: 271-311.

Bauer, M.E., T.E. Burk, A.R. Ek, P.R. Coppin, S.D. Lime, T.A. Walsh, D.K. Walters, W. Befort, and D.F Heinzen. 1994. Satellite inventory of Minnesota forest resources. Photogrammetric Engineering and Remote Sensing 60: 287-298.

Beaubien, J., and G. Simard. 1993. Méthodologie de classification des données AVHRR pour la surveillance du couvert végétal. Proceedings of the 16th Canadian Remote Sensing Symposium, Sherbrooke, Quebec, 7-10 June 1993: 597-603.

Beaubien, J., J. Cihlar, G. Simard, and R. Latifovic. 1998. Land cover from multiple Thematic Mapper scenes using a new enhancement - classification methodology. Journal of Geophysical Research (accepted).

Bischof, H., and A. Leonardis. 1998. Finding optimal neural networks for land use classification. IEEE Transactions on Geoscience and Remote Sensing 36 337-341.

Brown, J.F., T.R. Loveland, J.W. Merchant, B.C. Reed, and D.O. Ohlen. 1993. Using multisource data in global land cover characterization: concepts, requirements and methods: Photogrammetric Engineering and Remote Sensing 59: 977-987.

Carpenter, G.A. M.N. Gjaja, S. Gopal, and C.E. Woodcock. 1997. ART neural networks for remote sensing: vegetation classification from Landsat TM and terrain data. IEEE Transactions on Geoscience and Remote Sensing 35: 308-325.

Chavez, P. 1988. An improved dark-object subtraction technique for atmospheric scattering correction of multispectral data. Remote Sensing of Environment 24: 459-479.

Chavez, P. 1989. Radiometric calibration of Landsat Thematic Mapper multispectral images. Photogrammetric Engineering and Remote Sensing 55: 1285-1294.

Chen, J.M., and J. Cihlar. 1997. A hotspot function in a simple bidirectional reflectance model for satellite applications. Journal of Geophysical Research 102 (D22): 25,907-25,913.

Chuvieco, E., and R.G. Congalton. 1988. Using cluster analysis to improve the selection of training statistics in classifying remotely sensed data. Photogrammetric Engineering and Remote Sensing 54: 1275-1281.

Cihlar, J., 1996. Identification of contaminated pixels in AVHRR composite images for studies of land biosphere. Remote Sensing of Environment 56: 149-163.

Cihlar, J., and J. Beaubien. 1998. Land Cover of Canada 1995 Version 1.1. Digital data set documentation, Natural Resources Canada, Ottawa, Ontario.

Cihlar, J., J. Beaubien, Q. Xiao, J. Chen, and Z. Li. 1997a. Land cover of the BOREAS Region from AVHRR and Landsat data. Canadian Journal for Remote Sensing 23: 163-175.

Cihlar, J., H. Ly, Z. Li, J. Chen, H. Pokrant, and F. Huang. 1997b. Multitemporal, multichannel AVHRR data sets for land biosphere studies: artifacts and corrections. Remote Sensing of Environment 60: 35-57.

Cihlar, J., and J. Howarth. 1994. Detection and removal of cloud contamination from AVHRR composite images. IEEE Transactions on Geoscience and Remote Sensing 32: 427-437.

Cihlar, J., H. Ly, and Q. Xiao. 1996. Land cover classification with AVHRR multichannel composites in northern environments. Remote Sensing of Environment 58: 36-51.

Cihlar, J., Xiao, Q., Beaubien, J., Fung, K., and Latifovic, R. 1998a. Classification by Progressive Generalization: a new automated methodology for remote sensing multichannel data. International Journal for Remote Sensing 19: 2685-2704.

Cihlar, J., J. Chen, Z. Li, F. Huang, R. Latifovic, and R. Dixon. 1998b. Can interannual land surface signal be discerned in composite AVHRR data? Journal of Geophysical Research - Atmospheres 103: 23163-23172.

Cihlar, J., R. Latifovic, J. Chen, J. Beaubien, and Z. Li. 1998c. Selecting high resolution sample in land cover studies. Part 1: algorithm. Remote Sensing of Environment (submitted).

Cihlar, J., R. Latifovic, J. Chen, J. Beaubien, Z. Li, and S. Magnussen. 1998d. Selecting high resolution sample in land cover studies. Part 2: application to estimating land cover composition. Remote Sensing of Environment (submitted).

Cihlar, J., Latifovic, R., Chen, J,. and Li, Z. 1998e. Near-real time detection of contaminated pixels in AVHRR composites. Canadian Journal for Remote Sensing (submitted).

Cihlar, J., Manak, D., and Voisin, N., 1994a. AVHRR bidirectional reflectance effects and compositing. Remote Sensing of Environment 48:77-88.

Cihlar, J., Manak, D., and D'Iorio, M., 1994b. Evaluation of compositing algorithms for AVHRR data over land. IEEE Transactions for Geoscience and Remote Sensing 32 (2): 427-437.

Colwell, R.N. (Ed). 1960. Manual for photographic interpretation. The American Society of Photogrammetry, Washington, D.C. 868p.

Congalton, R.G. 1991. A review of assessing the accuracy of classifications of remotely sensed data. Remote Sensing of Environment 37: 35-46.

Congalton, R.G. 1996. Accuracy assessment: A critical component of land cover mapping. In: Scott, J.M., T.H. Tear, and F. Davis (Eds), Gap Analysis: A landscape approach to biodiversity planning. American Society for Photogrammetry and Remote Sensing, Bethesda, Maryland: 119-131.

Cracknell, A.P., and K. Paithoonwattanakij. 1989. Pixel and sub-pixel accuracy in geometrical image correction of AVHRR imagery. International Journal of Remote Sensing 10: 661-667.

De Boissezon, H., G. Gonzales, B. Pus, and M. Sharman. 1993. Rapid estimation of crop acreage and production at a European scale using high resolution imagery – operational review. Proceedings of the International Symposium ‘Operationalization of remote sensing’, ITC Enschede, The Netherlands: 94-105.

DeFries, R., M. Hansen, M. Steininger, R. Dubayah, R. Sohlberg, and J. Townshend. 1997. Subpixel forest cover in central Africa from multisensor, multitemporal data. Remote Sensing of Environment 60: 228-246.

DeFries, R.S., M. Hansen, and J.R.G. Townshend. 1995. Global discrimination of land cover types from metrics derived from AVHRR Pathfinder data. Remote Sensing of Environment 54: 209-222.

DeFries, R.S., M. Hansen, J.R.G. Townshend, and R. Sohlberg. 1998. Global land cover classification at 8 km spatial resolution: the use of training data derived from Landsat imagery in decision tree classifiers. International Journal for Remote Sensing 19 (in print).

DeFries, R.S., and J.R.G. Townshend. 1994. NDVI-derived land cover classification at global scales. International Journal for Remote Sensing 15: 3567-3586.

Dickinson, R.E., A. Henderson-Sellers, P.J. Kennedy, and M.F. Wilson. 1986. Biosphere-atmosphere transfer scheme (BATS) for the NCAR community climate model. NCAR Technical Note NCAR/TN275+STR, Boulder, CO. 69 p.

Driese, K.L., W.A. Reiners, E.H. Merrill, and K.G. Gerow. 1997. A digital land cover map of Wyoming, USA: a tool for vegetation analysis. Journal of Vegetation Science 8: 133-146.

Dubayah, R., B. Blair, J. Bufton, D. Clarke, J. JáJá, R. Knox, S. Luthcke, S. Prince, and J. Weishampel. 1997. The Vegetation Canopy Lidar mission. Presented at the Symposium on Land Satellite Information in the Next Decade II, American Society for Photogrammetry and Remote Sensing, Washington, D.C. <http://www.inform.umd.edu/Geography/vcl/>

Edwards, T.C. Jr., G.G. Moisen, and D.R. Cutler. 1998. Assessing map accuracy in a remotely sensed, ecoregion-scale cover map. Remote Sensing of Environment 63: 73-83.

Eidenshink, J.C., and J.L. Faundeen. 1994. The 1 km AVHRR global land data set: first stages in implementation. International Journal for Remote Sensing 15: 3443-3462.

Elvidge, C.D., D. Yuan, R.D. Weerackoon, and R.S. Lunetta. 1995. Relative radiometric normalization of Landsat Multispectral Scanner (MSS) data using an automatic scattergram-controlled regression. Photogrammetric Engineering and Remote Sensing 61: 1255-1260.

Emery, W.J., J. Brown, and Z.P. Nowak. 1989. AVHRR image navigation: summary and review. Photogrammetric Engineering and Remote Sensing 55: 1175-1183.

Eva, H.D., J.P. Malingreau, J.M. Gregoire, A.S. Belward, and C.T. Mutlow. 1998. The advance of burnt areas in Central Africa as detected by ATSR-1. International Journal of Remote Sensing 19: 1635-1637.

Foody, G.M. 1996. Approaches for the production and evaluation of fuzzy land cover classifications from remotely-sensed data. International Journal of Remote Sensing 17: 1317-1340.

Foody, G.M. 1998. Sharpening fuzzy classification output to refine the representation of sub-pixel land cover distribution. International Journal of Remote Sensing 19: 2593-2599.

Foody, G.M., R.M. Lucas, P.J. Curran, and M. Honzak. 1997. Non-linear mixture modeling without end-members using an artificial neural network. International Journal of Remote Sensing 18: 937-953.

Friedmann, D.E. 1981. Operational resampling for correcting images to a geocoded format. Proceedings of the Fifteenth International Symposium on Remote Sensing of Environment, Ann Arbor, MI: 195-199.

GCOS. 1997. GCOS/GTOS plan for terrestrial climate-related observations. Report GCOS-32, WMO/TD-No. 796, World Meteorological Organization. 130p.

Gong, P., D.J. Marceau, and P.J. Howarth. 1992. A comparison of spatial feature extraction algorithms for land-use classification with SPOT HRV data. Remote Sensing of Environment 40: 137-151.

Goward, S.N., B. Markham, D.G. Dye, W. Dulaney, and J. Yang. 1991. Normalized difference vegetation index measurements from the Advanced Very High Resolution Radiometer. Remote Sensing of Environment 35: 257-277.

Guindon, B. 1995. Utilization of Landsat Pathfinder data for the creation of large area mosaics. Proceedings of the 1995 ACSM/ASPRS Conference, Vol. 2, Charlotte, NC: 144-153

Guindon, B. 1997. Assessing the radiometric fidelity of high resolution image mosaics. ISPRS Journal of Photogrammetry and Remote Sensing 52: 229-243.

Gutman, G.G. 1994. Normalization of multi-annual global AVHRR reflectance data over land surfaces to common sun-target-sensor geometry. Advances in Space Research 14: (1)121-(1)124.

Gutman, G.G., A.M. Ignatov, and S. Olson. 1994. Towards better quality of AVHRR composite images over land: reduction of cloud contamination. Remote Sensing of Environment 50: 134-148.

Hammond, T.O., and D.L. Verbyla. 1996. Optimistic bias in classification accuracy assessment. International Journal of Remote Sensing 17: 1261-1266.

Hansen, M.C., R.S. DeFries, J.R.G. Townshend, and R. Sohlberg. 1998. Global land cover classification at 1 km spatial resolution using a classification tree approach. International Journal for Remote Sensing (submitted).

Hansen, M., R. Dubayah, and R. DeFries. 1996. Classification trees: an alternative to traditional land cover classifiers. International Journal of Remote Sensing 17: 1075-1081.

Holben B. 1986. Characteristics of maximum-value composite images from temporal AVHRR data. International Journal of Remote Sensing 7: 1417-1434.

Homer, C.G., R.D. Ramsey, T.C. Edwards Jr., and A. Falconer. 1997. Landscape cover-type modeling using a multi-scene Thematic Mapper mosaic. Photogrammetric Engineering and Remote Sensing 63: 59-67.

Hord, R.M., and W. Brooner. 1976. Land-use map accuracy criteria. Photogrammetric Engineering and Remote Sensing 42: 671-677.

IGBP. 1990. The International Geosphere-Biosphere Programme: a study of global change. The initial core projects. IGBP report #12, Stockholm, Sweden.

Iverson, L.R., E.A. Cook, and R.L. Graham. 1994. Regional forest cover estimation via remote sensing: the calibration center concept. Landscape Ecology 9: 159-174.

James, M.E., and S.N.V. Kalluri. 1994. The Pathfinder AVHRR land data set: an improved coarse resolution data set for terrestrial monitoring. International Journal of Remote Sensing 15: 3347-3364.

Jennings, M.D. 1995. Gap Analysis today: A confluence of biology, ecology, and geography for management of biological resources. Wildlife Society Bulletin 23:658-662.

Kalkhan, M.A., R.M. Reich, and T.J. Stohlgren. 1998. Assessing the accuracy of Landsat Thematic Mapper classification using double sampling. International Journal of Remote Sensing 19: 2049-2060.

Kartikeyan, B., A. Sarkar, and K.L. Majumder. 1998. A segmentation approach to classification of remote sensing imagery. International Journal of Remote Sensing 19: 1695-1709.

Kelly, P.M., and J.M. White. 1993. Preprocessing remotely-sensed data for efficient analysis and classification. In: Knowledge-based systems in aerospace and industry: applications of artificial intelligence, SPIE Proceedings: 24-30.

Laporte, N.T., S.J. Goetz, C.O. Justice, and M. Heinecke. 1998. A new land cover map of central Africa derived from multi-resolution, multi-temporal AVHRR data. International Journal of Remote Sensing 19: 3537-3550.

Lark, R. M. 1995a. A reappraisal of unsupervised classification, I: correspondence between spectral and conceptual classes. International Journal of Remote Sensing 16: 1425-1423.

Lark, R. M. 1995b. A reappraisal of unsupervised classification, II: optimal adjustment of the map legend and a neighbourhood approach for mapping legend units. International Journal of Remote Sensing 16: 1445-1460.

Leroy, M. 1994. Compositing reflectance measured from space for vegetation monitoring. Proceedings of the Sixth International Symposium on Physical Measurements and Signatures in Remote Sensing, 17-21 January, Val d'Isere, France: 21-32.

Li, Z., J. Cihlar, X. Zhang, L. Moreau, and H. Ly. 1996. The bidirectional effects of AVHRR measurements over boreal regions. IEEE Transactions on Geoscience and Remote Sensing 34: 1308-1322.

Li, Z., and H.G. Leighton. 1992. Narrowband to broadband conversion with spatially autocorrelated reflectance measurements. Journal of Applied Meteorology 31: 421-432.

Lillesand, T.M. 1996. A protocol for satellite-based land cover classification in the Upper Midwest. Pages 103-118 in J.M. Scott, T.H. Tear, and F. Davis, editors. Gap Analysis: A landscape approach to biodiversity planning. American Society for Photogrammetry and Remote Sensing, Bethesda, Maryland.

Liu, J., Chen, J.M., Cihlar, J., and Park, W. 1997. A process-based boreal ecosystem productivity simulator using remote sensing inputs. Remote Sensing of Environment 62: 158-175.

Loveland, T.R., and A. S. Belward. 1997. The IGBP-DIS global 1 km land cover dataset, DISCover: first results. International Journal of Remote Sensing 18: 3289-3295.

Loveland, T.R., J.W. Merchant, J.F. Brown, D.O. Ohlen, B.C. Reed, P. Olson, and J. Hutchinson. 1995. Seasonal land-cover regions of the United States. Annals of the Association of American Geographers 85: 339-355.

Loveland, T.R., B.C. Reed, J.F. Brown, D.O. Ohlen, Z. Zhu, L. Yang, and J.W. Merchant. 1999. Development of a global characteristics land cover database and IGBP DISCover from 1-km AVHRR data. International Journal of Remote Sensing, this issue.

Loveland, T.R., J.W. Merchant, D.O. Ohlen, and J.F. Brown. 1991. Development of a land-cover characteristics database for the conterminous U.S. Photogrammetric Engineering and Remote Sensing 57: 1,453-1,463.

Los, S.O., C.O. Justice, and C.J. Tucker. 1994. A global 1^o by 1^o NDVI data set for climate studies derived from the GIMMS continental NDVI data. International Journal of Remote Sensing 15: 3493-3518.

Magnussen, S. 1997. Calibrating photo-interpreted forest cover types and relative species compositions to their ground expectations. Canadian Journal of Forest Research 27: 491-500.

Mannan, B., J. Roy, and A.K. Ray. 1998. Fuzzy ARTMAP supervised classification of multi-spectral remotely-sensed images. International Journal of Remote Sensing 19: 767-774.

Martonchik, J.V., D.J. Diner, B. Pinty, M.M. Verstraete, R.B. Myneni, Y. Knyazikhin, and H.R. Gordon. 1998. Determination of land and ocean reflective, radiative and biophysical properties using multiangle imaging. IEEE Transactions on Geoscience and Remote Sensing 36: 1266-1281.

Mathews, E. 1983. Global vegetation and land use: new high resolution data bases for climate studies. Journal of Climate and Applied Meteorology 22: 474-487.

Mayaux, P., and E. Lambin. 1995. Estimation of tropical forest area from coarse spatial resolution data: a two-step correction function for proportional errors due to spatial aggregation. Remote Sensing of Environment 53: 1-16.

Mayaux, P., and E.F. Lambin. 1997. Tropical forest area measured from global land-cover classifications: inverse calibration models based on spatial textures. Remote Sensing of Environment 59: 29-43.

Mayaux, P., F. Achard, and J.-P. Malingreau. 1998. Global tropical forest area measurements derived from coarse resolution satellite imagery: a comparison with other approaches. Environmental Conservation 25: 37-52.

Moody, A., and C.E. Woodcock. 1996. Calibration-based models for correction of area estimates derived from coarse resolution land-cover data. Remote Sensing of Environment 58: 225-241.

NASA. 1982. LANDSAT-4 World Reference System (WRS) User Guide. National Aeronautics and Space Administration, Goddard Space Flight Center, Greenbelt, MD.

Nishihama, M., R.E. Wolfe, D. Solomon, F. Patt, J. Blanchette, A. Fleig, and E. Masuoka. 1997. MODIS Level 1A earth location: Algorithm Theoretical Basis Document. Report SDST-092, Laboratory for Terrestrial Physics, NASA Goddard Space Flight Center, Greenbelt, MD.

Olson, J.S., J. Watts, and L. Allison. 1983. Carbon in live vegetation of major world ecosystems. Report W-7405-ENG-26, U.S. Department of Energy, Oak Ridge National Laboratory.

O'Neill, R.V., J.R. Krummel, R.H. Gardner, G. Sugihara, B. Jackson, D.L. DeAngelis, B.T. Milne, M.G. Turner, B. Zygmunt, S.W. Christensen, V.H. Dale, and R.L. Graham. 1988. Indices of landscape pattern. Landscape Ecology 1: 153-162.

PCI. 1998. ORTHOENGINE. PCI Software Package, PCI Inc., Toronto, ON, Canada.

Pokrant, H. 1991. Land cover map of Canada derived from AVHRR images. Manitoba Remote Sensing Centre, Winnipeg, MB, Canada.

Qi. J., and Y. Kerr. 1994. On current compositing algorithms. Proceedings of the Sixth International Symposium on Physical Measurements and Signatures in Remote Sensing, 17-21 January, Val d'Isere, France: 135-142.

Rabben, E.L. 1960. Fundamentals of photo interpretation. In: Colwell, R.N. (Ed.), Manual of photographic interpretation, The American Society of Photogrammetry, Washington, D.C.: 99-168.

Robertson, B., A. Erickson, J. Friedel, B. Guindon, T. Fisher, R. Brown, P. Teillet, M. D'Iorio, J. Cihlar, and A. Sancz. 1992. GEOCOMP, A NOAA AVHRR Geocoding and Compositing System. Proceedings of the ISPRS Conference, Commission 2, Washington, D.C.: 223-228.

Rosenfield, G.H., and K. Fitzpatrick-Lins. 1986. A coefficient of agreement as a measure of thematic classification accuracy. Photogrammetric Engineering and Remote Sensing 52: 223-227.

Running, S.W., C.O. Justice, V. Salomonson, D. Hall., J. Barker. Y.J. Kaufmann, A.H. Strahler, A.R. Huette, J.-P. Muller, V. Vanderbilt, Z.M. Wan, P. Teillet, and D. Carneggie. 1994. Terrestrial remote sensing science and algorithms planned for EOS/MODIS. International Journal of Remote Sensing 15: 3587-3620.

Running, S.W., T.R. Loveland, L.L. Pierce, R.R. Nemani, and E.R. Hunt Jr. 1995. A remote sensing based vegetation classification logic for global land cover analysis. Remote Sensing of Environment 51: 39-48.

Saint, G. 1992. “VEGETATION onboard SPOT 4: mission specifications. Report No. 92102, Laboratoire d’etudes et de recherches en teledetection spatiale, Toulouse, France. 40p.

Salomonson, V.V., W. L. Barnes, P.W. Maymon, H.E. Montgomery, and H. Ostrow. 1989. MODIS: advanced facility instrument for studies of the Earth as a system. IEEE Transactions on Geoscience and Remote Sensing 27: 145-153.

Schott, J.R., C. Salvaggio, and W.J. Volchok. 1988. Radiometric scene normalization using pseudoinvariant features. Remote Sensing of Environment 26: 1-16.

Sellers, P.J., S.O. Los, C.J. Tucker, C.O. Justice, D.A. Dazlich, J.A. Collatz, and D.A. Randall. 1994. A global 1^o by 1^o NDVI data set for climate studies. Part 2: The generation of global fields of terrestrial biophysical parameters from the NDVI. International Journal of Remote Sensing 15: 3519-3545.

Sellers, P.J., D.A. Randall, G.J. Collatz, J.A. Berry, C.B. Field, D.A. Dazlich, C. Zhang, G.D. Collelo, and L. Bounoua. 1996. A revised land surface parameterization (SiB2) for atmospheric GCMs - Part I-model formulation: Journal of Climate 9: 676-705.

Shimabukuro, Y.E., E.M.K. Mello, J.C. Moreira, and V. Duarte. 1997. Segmentacao e classificacao da imagem sombra do modelo de mistura para mapear desflorestamento na Amazona. Report INPE-6147-PUD/029, Instituto Nacional de Pesquisas Espacias, Sao Jose dos Campos, Brazil. 16p.

Staenz, K., R.J. Brown, and P.M. Teillet. 1984. Influence of the viewing geometry on vegetation measures. Proceedings of the 8th Canadian Symposium on Remote Sensing, Montreal, QUE, May 3-6: 5-12.

Steyaert, L. T., F.G. Hall, and T.R. Loveland. 1997. Land cover mapping, fire regeneration, and scaling studies in the Canadian boreal forest with 1 km AVHRR and Landsat TM data. Journal of Geophysical Research 102: 29581-29598.

Thomas, I.L., and G. McK. Allcock. 1984. Determining the confidence level for a classification. Photogrammetric Engineering and Remote Sensing 50: 1491-1496.

Townshend, J.R.G., C.O. Justice, D. Skole, J.-P. Malingreau, J. Cihlar, P. Teillet, F. Sadowski, and S. Ruttenberg. 1994. The 1 km resolution global data set: needs of the International Geosphere - Biosphere Programme. International Journal of Remote Sensing 15: 3417-3441.

Van der Meer, F. 1995. Spectral unmixing of Landsat Thematic Mapper data. International Journal of Remote Sensing 16: 3189-3194.

Viovy, N., O. Arino, and A.S. Belward. 1992. The Best Index Slope Extraction (BISE): a method for reducing noise in NDVI time-series. International Journal of Remote Sensing 13: 1585-1590.

Vogelmann, J.E., T. Sohl, and S.M. Howard. 1998. Regional characterization of land cover using multiple sources of data. Photogrammetric Engineering and Remote Sensing 64: 45-57.

Walsh, T.A., and T.E. Burk. 1993. Calibration of satellite classifications of land area. Remote Sensing of Environment 46: 281-290.

Wigmosta, M.S., L.W. Vail, and D.P. Lettenmaier. 1994. A distributed hydrology-vegetation model for complex terrain. Water Resources Research 30: 1665-1679.

Wu, A., Z. Li, and J. Cihlar. 1995. Effects of land cover type and greenness on AVHRR bidirectional reflectances: analysis and removal. Journal of Geophysical Research 100:9179-9192.

Yool, S.R. 1998. Land cover classification in rugged areas using simulated moderate-resolution remote sensor data and an artificial neural network, International Journal of Remote Sensing 19: 85-96.

Yuan, D., and C.D. Elvidge. 1996. Comparison of relative radiometric normalization techniques. ISPRS Journal of Photogrammetry and Remote Sensing 51: 117-126.

Zhu, Z., and D.L. Evans. 1994. U.S. forest types and predicted percent forest cover from AVHRR data. Photogrammetric Engineering and Remote Sensing 60: 525-531.

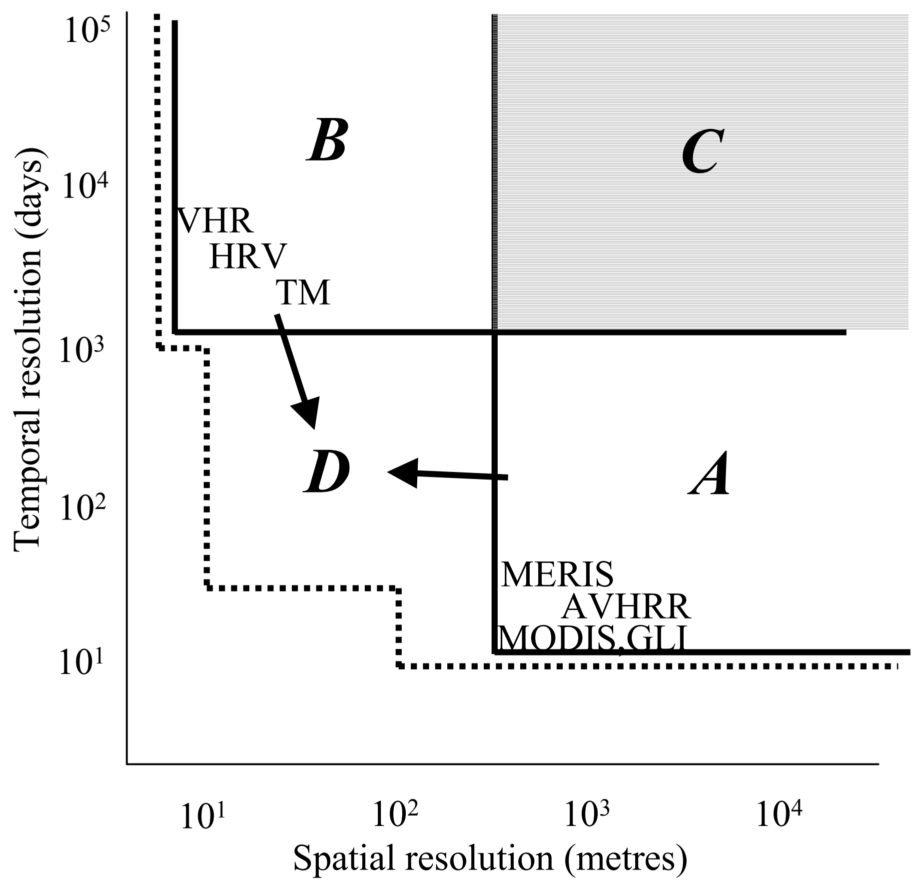

Figure 1. Land cover mapping requirements expressed in spatial and temporal resolutions. The acronyms represent current or future satellite sensors at both fine and coarse resolutions; VHR represents future very high resolution sensors, now being prepared for launch by several private companies.

OPERATION	***FINE RESOLUTION***	***COARSE RESOLUTION***
GEOMETRIC CORRECTIONS		
COMPOSITING	BY SCENE (CLEAR-SKY ONLY)	BY PIXEL (ALL DATA)
RADIOMETRIC CORRECTIONS	◆ATMOSPHERIC ◆RADIOMETRIC ADJUSTMENTS	◆ATMOSPHERIC ◆BIDIRECTIONAL ◆RESIDUAL CONTAMINATION
CLASSIFIC-ATION	CASE I	CASE II
ACCURACY ASSESSMENT		

Figure 2. Major steps in extracting land cover information using satellite data at fine and coarse resolutions. See text for discussion.

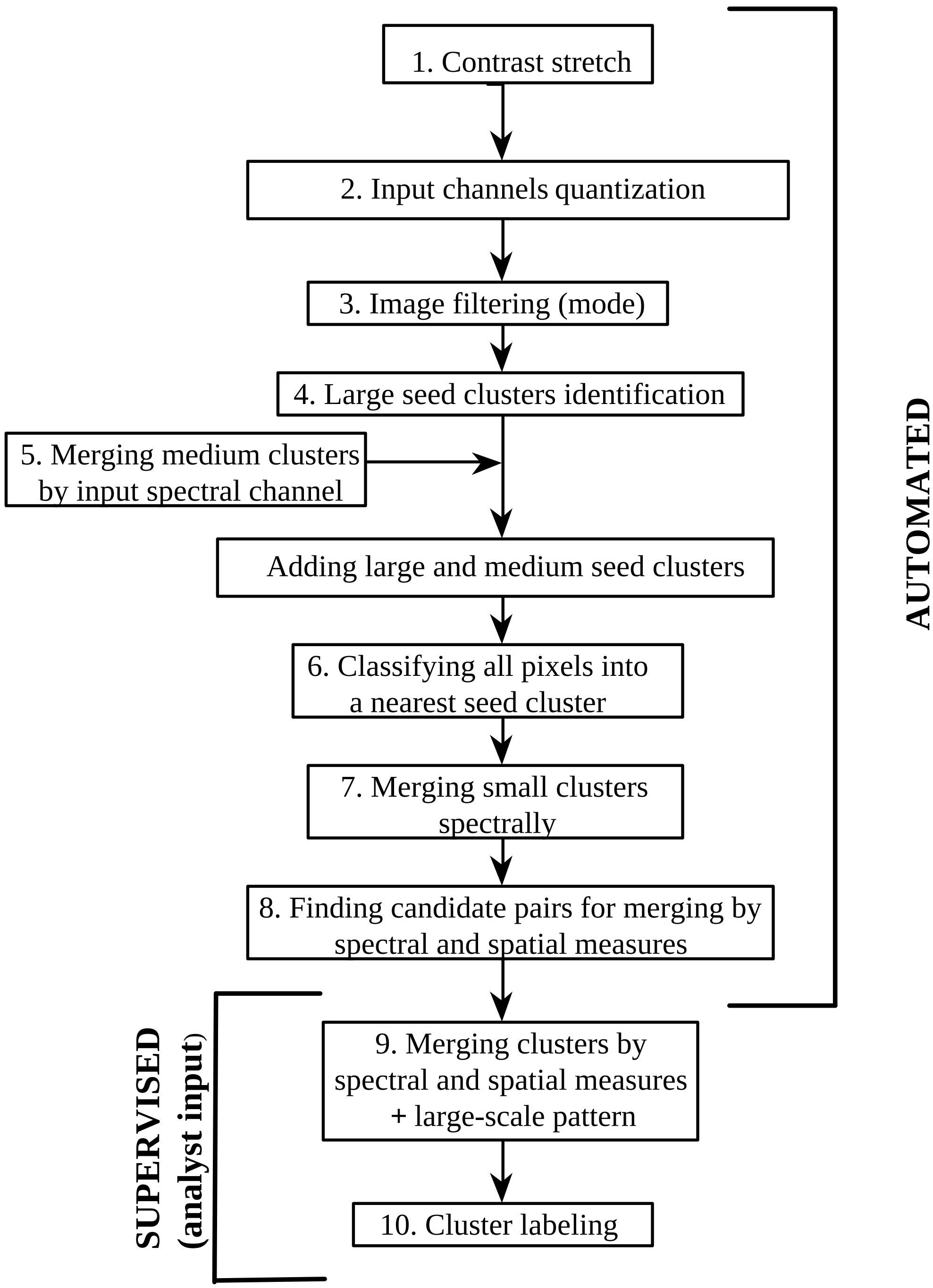

Figure 3. Flowchart for Classification by Progressive Generalization (CPG; Cihlar et al., 1998a). In this unsupervised classification, steps 1-8 can be carried out in an automated mode but steps 9-10 require analyst's input. CPG assumes that any of the initial spectral values might represent a significant land cover class; the task is therefore to optimally group these values into a small number of final clusters. Steps 1-3 reduce the number of spectral combinations, without visually degrading the input image; steps 4-5 identify important clusters; and steps 7-9 allow merging of increasingly dissimilar clusters using spectral and spatial similarity measures.