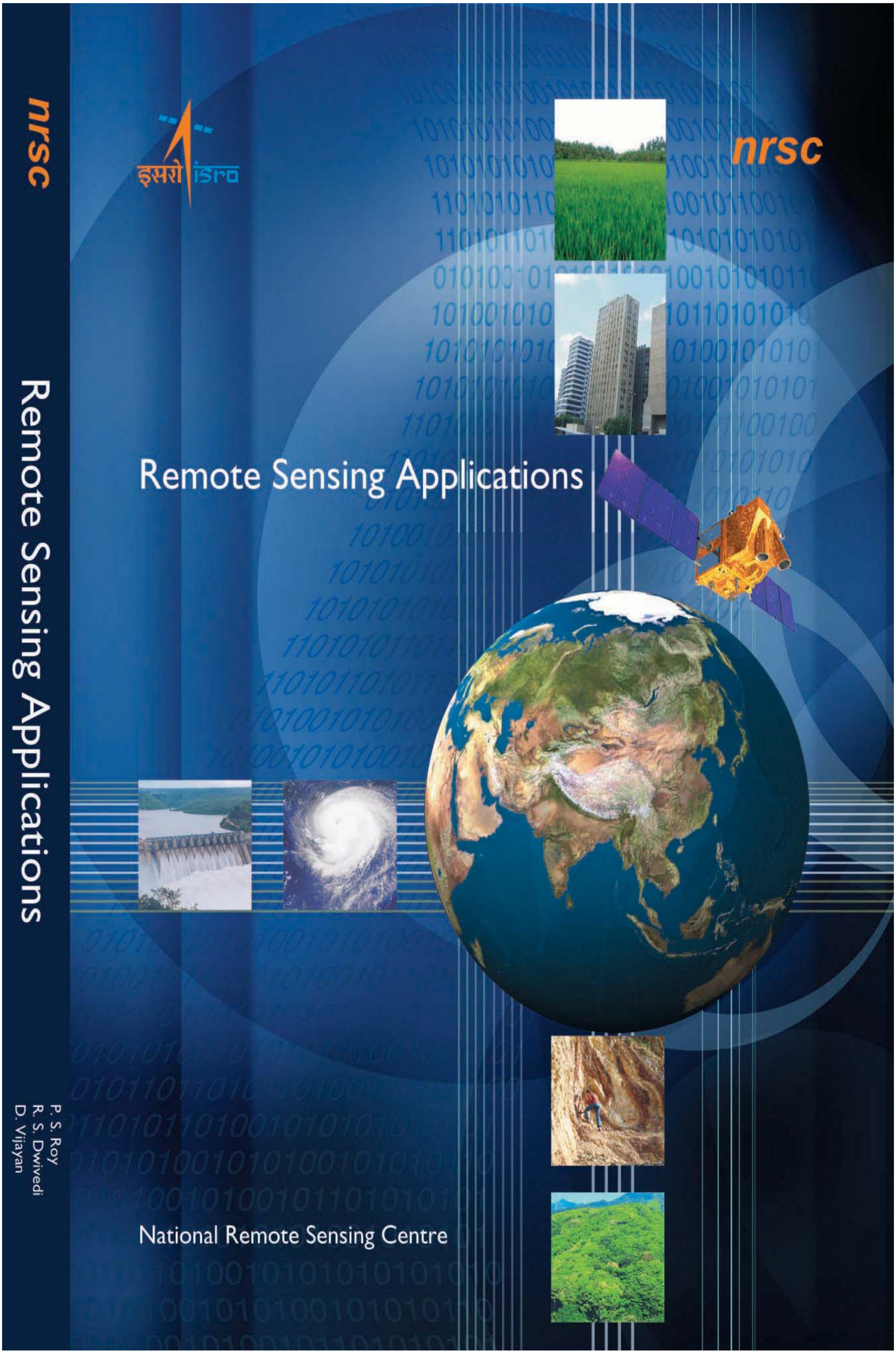
nrsc
Remote Sensing Applications
P. S. Roy
R. S. Dwivedi
D. Vijayan
इसरो isro
nrsc
Remote Sensing Applications
National Remote Sensing Centre

Remote Sensing Applications

Land Use and Land Cover Analysis

2.1. Introduction

Economic development and population growth have triggered rapid changes to Earth's land cover over the last two centuries, and there is every indication that the pace of these changes will accelerate in the future. These rapid changes are superposed on long-term dynamics associated with climate variability. Land cover change can affect the ability of the land to sustain human activities through the provision of multiple ecosystem services and because the resultant economic activities cause feedbacks affecting climate and other facets of global change. Accordingly, systematic assessments of Earth's land cover must be repeated, at a frequency that permits monitoring of both long-term trends as well as interannual variability, and at a level of spatial detail to allow the study of human-induced changes.

Land cover, defined as the assemblage of biotic and abiotic components on the Earth's surface, is one of the most crucial properties of the Earth system. There are three fundamental ways in which it is important (Turner *et al.*, 1994). The first lies in the interaction of land cover with the atmosphere, which leads to regulation of the hydrologic cycle and energy budget, and as such is needed both for weather and climate prediction (DeFries *et al.*, 2002). For example, most climate models are now coupled with Land Surface Parameterizations (LSPs) which use digital land cover data to produce databases of albedo, surface roughness, evapotranspiration and respiration. Second, land cover plays a major role in the carbon cycle acting as both sources and sinks of carbon. In particular, the rates of deforestation, afforestation and regrowth play a significant role in the release and sequestering of carbon and consequently affect atmospheric CO_2 concentration and the strength of the greenhouse effect (IPCC, 2000; Janetos and Justice, 2000; Houghton, 1999). Finally, land cover also reflects the availability of food, fuel, timber, fiber, and shelter resources for human populations, and serves as a critical indicator of other ecosystem services such as biodiversity. Information on land cover is fundamental to many national/global applications including watershed management and agricultural productivity. Thus, the need to monitor land cover is derived from multiple intersecting drivers, including the physical climate, ecosystem health, and societal needs.

Although the terms "land cover (LC)" and "land use (LU)" are sometimes used interchangeably, they are actually different. Simply put, land cover is what covers the surface of the earth and land use describes how the land is used. Examples of land cover classes include: water, snow, grassland, deciduous forest, and bare soil. Land use examples include: wildlife management area, agricultural land, urban, recreation area etc. Two land parcels may have similar land cover, but different land use. For instance, A golf course and an office building are both commercial land uses. The former would have a land cover of grass, while the latter would be considered built up.

2.2. LULC Mapping

2.2.1. Conventional Approach

Compilation from revenue records by the Directorate/Bureau of Economic and Statistics (DES/BES) of respective states has been the conventional approach of collecting LULC information in the country. The land use information "derived" from the agricultural inventory carried out at individual plot level is available in a nine-fold classification system. These data are available in the form of statistical records without any reference to the spatial locations. Topographical maps from Survey of India that represent very broad land use categories mapped using mainly ground information on 1:50,000 to 1:25,000 scale is another source of LULC information. However, this land use information does not represent current situation of land use and also does not reflect changes. Land use maps generated by Soil Survey organizations that are based on soil mapping units forms another source, from which land use information can be deciphered. However, such maps are generated and available for only specific project areas. For most part, they have worked independently and without coordination with other agencies. Too often this has meant duplication of effort, or it has been found that data collected for a specific purpose were of little or no value for a similar purpose only a short time later.

There are many different sources of information on existing land use and land cover and on changes that are occurring at different levels. Local planning agencies make use of detailed information generated during ground surveys involving enumeration and observation. Major problems that surface during the application and interpretation of these data sets include changes in definitions of categories and data collection methods by source agencies, incomplete data coverage, varying data age, and employment of incompatible classification systems. In addition, it is nearly impossible to aggregate the available data because of the differing classification systems used. These limitations of traditional approaches had been partly overcome by adopting modern approaches like remote sensing.

2.2.2. Remote Sensing based Approach

Land cover mapping is a product of the development of remote sensing, initially through aerial photography. Remote sensing technology, because of the benefits it offers (wide area coverage, frequent revisits, multispectral**,** multisource**,** and storage in digital format to facilitate subsequent updating and compatibility with GIS technology) proved very practical and economical means for an accurate classification of land cover.

There are several important considerations that determine the characteristics of land cover information generated using remote sensing data.

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, land use inventories, forest inventories, planning as well as other biophysical resource inventories require land cover information. Specific models of vegetation–atmosphere interactions require different types of land cover information (Dickinson *et al.*, 1986, Sellers *et al.*, 1994) including productivity models (Liu *et al.*, 1997) and hydrological models (Wigmosta *et al.*, 1994)

Thematic content: The information may be needed for few cover types (e.g., forest–non-forest); for all cover types and at the same (or varying) levels of detail; tailored to specific model requirements; or as continuous variables (e.g., percentage coniferous forest). The thematic content also has a strong effect on the frequency of land cover mapping

Scale: Over large areas, land cover information may be required locally (at specific sites), at regional scales, or continental to global scales

Data: The quality and availability of remote sensing data limit the type and accuracy of information that may be extracted

Processing and analysis techniques: The characteristics of processing and analysis techniques employed at various stages are of critical importance

2.2.3. LULC Classification System

There is no one ideal classification of land use and land cover, and it is unlikely that one could ever be developed. There are different perspectives in the classification process, and the process itself tends to be subjective, even when an objective numerical approach is used. There is, in fact, no logical reason to expect that one detailed inventory should be adequate for more than a short time, since land use and land cover patterns change in keeping with demands for natural resources. Each classification is made to suit the needs of the user.

In order to address the issues associated with classification like class definitions, multiple land uses on a single land parcel, minimum representable area and to standardize the LULC information that could be generated using remote sensing data. Anderson (1971) developed some criteria for classification systems.

- The minimum level of interpretation accuracy in the identification of land use and land cover categories from remote sensor data should be at least 85 percent
- The accuracy of interpretation for the several categories should be about equal
- Repeatable or repetitive results should be obtainable from one interpreter to another and from one time of sensing to another
- The classification system should be applicable over extensive areas
- The categorization should permit vegetation and other types of land cover to be used as surrogates for activity
- The classification system should be suitable for use with remote sensor data obtained at different times of the year
- Effective use of subcategories that can be obtained from ground surveys or from the use of larger scale or enhanced remote sensor data should be possible
- Aggregation of categories must be possible

- Comparison with future land use data should be possible
- Multiple uses of land should be recognized when possible

Accordingly, he proposed a multilevel land use and land cover classification system, wherein LULC information at Levels I and II would generally be of interest to users who desire data on a nationwide, interstate, or statewide basis. More detailed land use and land cover data such as those categorized at Levels III and IV usually will be used more frequently by those who need and generate local information at the intrastate, regional or municipal level. It was intended that these latter levels of categorization would be developed by the user groups themselves, so that their specific needs might be satisfied by the categories they introduced into the structure. The system satisfied the three major attributes of the classification process (1) it gave names to categories by simply using accepted terminology; (2) it was amenable to further refinement on the basis of more extended and varied use and (3) it allowed inductive generalizations to be made. At the more generalized levels it met the principal objective of providing a land use and land cover classification system for use in land use planning and management activities.

Later on, many refinements and customizations were effected in the LULC classification systems, commensurating with the needs of users and it is beyond the scope of this chapter to discuss the LULC classification systems developed all over the globe.

2.3. Historical perspective of LULC mapping projects using remote sensing in India

The Indian experience on use of satellite data for LULC analysis is mentioned in the Manual on National land Use Mapping at 1:250000 scale using IRS-P6 AWiFS data (NRSA, 2004), The work was carriedout by National Remote Sensing Centre (erstwhile NRSA). Department of Space, Government of India, in collaboration with various central and state government organisations. Realizing the need for an up-to-date nationwide LULC maps by several departments in the country, as a prelude, a LULC classification system with 24 categories up to Level-II, suitable for mapping on 1:250,000 scale, was developed by NRSC by taking into consideration the existing land use classification adopted by NATMO, CAZRI, Ministry of Agriculture, Revenue Department, AIS & LUS, etc., and the details obtainable from satellite imagery. After discussions with nearly 40 user departments / institutions in the country a 22 fold classification system was finalized and adopted for Nationwide LULC Analysis.

2.3.1. Nationwide LULC Analysis for Agro-Climatic Zone Planning

The district-wise LULC analysis of all the 15 agro-climatic zones, using the 22 fold LULC classification system was completed using satellite data for the period 1988 – 89. The IRS - LISS-I data of kharif (July-October) 1988 and Rabi (November– March) 1989 were used to generate details on crop land in Kharif (July-October) and Rabi seasons, the area under double crop, fallow lands, different types of forests, degradation status, wasteland, water bodies, etc., using hybrid methodology i.e., visual as well as digital analysis approach. NRSC along with Regional Remote Sensing Centres (RRSC's), State Remote Sensing Centres and other institutions completed this task. Out of 442 districts in the country, 274 districts were analyzed using visual techniques and remaining 168 districts by digital techniques. The Planning Commission of India was the main user for this project.

2.3.2. National Wastelands Inventory Project (NWIP)

Until recently, no attempt had been made to prepare map showing different types of wastelands in India. The area reported by various government agencies under wastelands varies from 38 M ha, to 175M. ha. In 1985, NRSC prepared wasteland maps of all states and union territories at a 1:1 million scale. The total area of wastelands in the country during 1980 – 1982 was estimated at 53.3 million ha or 16.2 per cent of the geographical area of the country.

The National Wastelands Development Board (NWDB) was setup in 1985 with an objective of rehabilitating 5 million ha of land each year for fuel wood and fodder production through a massive programme of seeding and afforestation. This programme required a very reliable database that provided details on the type, extent, location and ownership of wastelands. In view of varying estimates of the extent of wasteland, including the one provided by NRSC based on remote sensing, the need for precise definitions of various categories of wastelands realized. The Technical Task Force established by the NWDB proposed a classification system consisting of thirteen categories of wastelands.

Subsequently waste land mapping on 1 : 50,000 scale was taken up in five phases and about 5000 wasteland maps covering entire country were prepared. The methodology developed based on pilot studies were used for identification and delineation of different types of wastelands using satellite data. Both Landsat Thematic Mapper (TM) and an Indian satellite (LISS-II and LISS-III) data were used for mapping purposes. Hybrid methodology i.e., both visual and digital techniques were used to derive information on the wastelands. About 63,87 million ha (20.17 per cent) have been estimated as wastelands through this study. Second cycle wasteland analysis has been completed using 2003 satellite data. An estimated 55.27 million ha. (17.45%) of land area has been mapped as wastelands. Currently, the 3rd cycle of mapping is in progress.

2.3.3. National Natural Resource Census

Land Use and Land Cover (IRS AWiFS data) : A composite Land Use/ Land Cover data set has been generated using multi temporal IRS-AWiFs data. Analysis is being carried out on 1: 250, 000 scale using level I and some Level II classes of land use classification. This project was aimed to analyse annual land use distribution for next three years i.e., 2004-05, 2005-06 and 2006-07.

Land Use / Land Cover inventory using IRS P6 LISS III data: Under the national level Project, LULC mapping on 1:50,000 scale for entire country has been taken up after conducting prototype studies for development of legend, standardization of methodology including digital data base creation and to generate spatial statistics. These studies are being carried out using 2005-06 databases to create the bench mark database which can later be used to understand the degree and magnitude of LULC changes at time intervals of 5 years.

2.4. Methodology of Land Use / Land Cover Analysis

In principle, land cover mapping from satellite data is straightforward and consists of four steps: data acquisition, pre-processing, analysis/classification, product generation and documentation.

2.4.1. Pre-processing

In principle, it entails geometric and radiometric corrections. Geometric corrections will not be discussed here as it is beyond the scope of present topic. Details on radiometric corrections is presented in the subsequent paragraphs.

Coarse resolution data:

In the past, some classification projects employing coarse resolution data were carried out with single-date, relatively cloud-free images. 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 to ensure consistency across the mapped area. For these reasons, research in recent years has emphasised the use of image composites.

In a compositing process, the image product is prepared so as to contain, as far as possible, information about the land surface itself. Since a large fraction of the pixels typically contain 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 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. The pixel compositing approach yields nominally cloud-free composites every few 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.

The degree of corrections following compositing varies among investigations. Atmospheric corrections are frequently carried out, 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 clouds, haze, or snow patches, 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 modeled. 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.,* 1999). Bidirectional corrections are possible but have not yet been frequently implemented because of the perceived complexity of the problem.

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., a mosaic of scenes), the situation is more complicated. In principle, two options are possible. 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 labelling 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, case I is highly flexible and can cope with various limitations of the input data.

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 (TM) or Satellite Probatoire d'Observation de la Terre High Resolution Visible Imaging System (SPOT HRV) in nadir mode.

A 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. These corrections have been carried out interactively or they can be automated (Chavez ,1988, Schott *et al.,* 1988, Elvidge *et al.,* 1995, Atzberger,1996, Yuan and Elvidge, 1996, Guindon, 1995). However, reconciling adjacent scenes may not be sufficient in larger scene composites. 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. 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), 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 yet been explored. In principle, it requires pre-processing 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. 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 the 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.

2.4.2. Classification

Land cover information that can be gleaned from satellite images is the spectral and spatial attributes of individual cover types, There are some differences between 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.

2.4.2.1. Digital Classification

Numerical techniques for satellite image classification have a long tradition, dating back to at least the early 70s, 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 (Foody *et al.*, 1997), fuzzy classification (Foody, 1998, Mannan *et al.*, 1998) and mixture modeling (van der Meer, 1995) for supervised classification; and classification by progressive generalization(Cihlar *et al.*,1998e),classification through enhancement, and post- processing adjustments (Lark 1995 a, 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, although a supervised method has also been used in such case (Hansen *et al.*, 2000). Unsupervised classification provides 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), 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 (Homer *et al.*, 1997, Cihlar *et al.*, 1998e, 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. 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 both the supervised and unsupervised method. The important advantage of the latter is that concerns about the location and representativeness of the ground data are much reduced because the clusters are homogenous by definition.

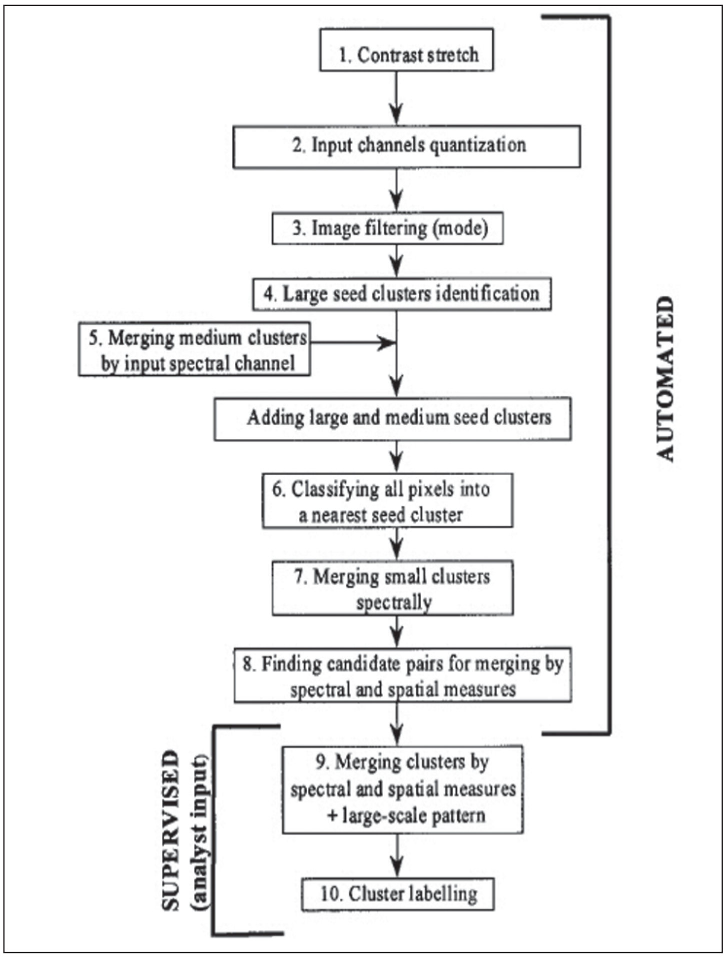

Figure 2.1: Flowchart for Classificationby Progressive Generalization (source: Cihlar et al., 1998)

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 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 (perfield classifiers), and in other ways. Given the fact that spatial attributes can aid 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.,* (1998) 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 2.1), 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) without the need for ground information.

Over large areas, applications of frequent mapping and at high spatial resolution are rare 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. Figure 2.2 illustrates the Lan Use/Land Cover map generated through digitatal classification using multispectral satellite data.

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),

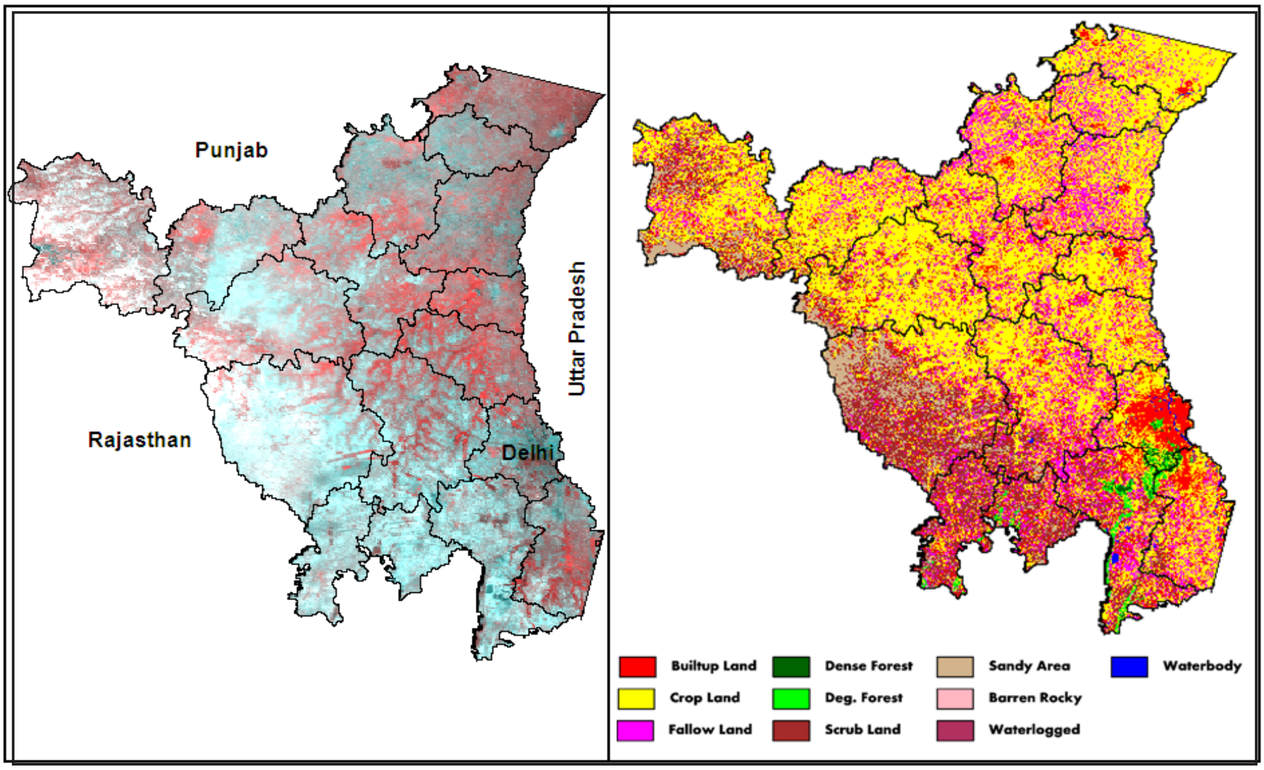

Figure 2.2: Land Use/ Land Cover Map of Haryana State generated through digital supervised classification technique from IRS-WiFS image of February 2002

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.

2.4.2.2. Manual Classification

Manual, or visual, classification of remotely sensed data is an effective method of classifying land cover especially when the analyst is familiar with the area being classified. This method uses skills that were originally developed for interpreting aerial photographs. It relies on the interpreter to employ visual cues such as tone, texture, shape, pattern, and relationship to other objects to identify the different land cover classes (figure 2.3), The primary advantage of manual interpretation is its utilization of the brain to identify features in the image and relate them to features on the ground. The brain can still beat the computer in accurately identifying image features. Another advantage is that manual classification can be done without a computer, instead using a hardcopy version of a satellite image.

The downside of manual interpretation is that it tends to be tedious and slow when compared with automated classification and because it relies solely on a human interpreter it is more subjective. Another drawback is that it is only able to incorporate 3 bands of data from a satellite image since the interpretation is usually done using a color image comprised of red, green, and blue primary colours.

The technique used in manual interpretation is fairly simple. The analyst views the image on either a computer screen or a hardcopy printout and then draws a polygon around areas that are identified as a particular land cover type. If the land cover delineations are done on a computer screen the land cover map is created during the delineation process. If the interpretation is done on a hardcopy image the resulting map will have to be digitized to convert it into a machine readable format.

2.4.2.3. Hybrid Approach

A hybrid approach combines the advantages of the automated and manual methods to produce a land cover map that is better than if just a single method was used. One hybrid approach is to use one of the automated classification methods to do an initial classification and then use manual methods to refine the classification and correct

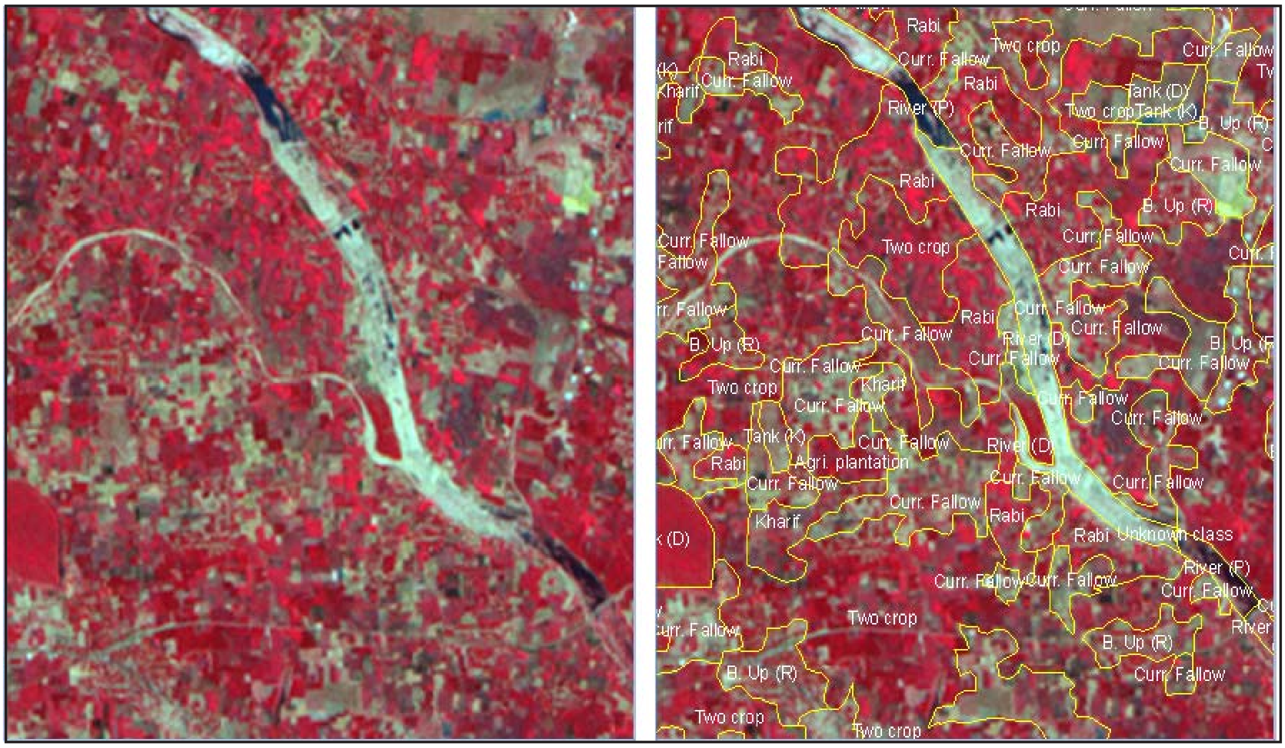

Figure 2.3: Land use /Land Cover map of part of Karaikal, Pondichery generated using manual classification Heads-Up digitisation approach. The FCC pertains to IRS-P6 LISS-III data of February, 2006

obvious errors. With this approach a reasonably good classification can be obtained quickly with the automated approach and then manual methods can be used to refine the classes that did not get labeled correctly.

The editing process requires that the analyst be able to compare the classified map with either the original satellite image or some other imagery that can be used to identify land cover features. To compare a classified map with imagery it is helpful to have access to software that allows the analyst to flicker between two images (the land cover image and the original satellite image) or slide one image over the other on the computer display using a technique often called “swiping”. By doing these comparisons the analyst gets a sense of the quality of the classification. When errors are spotted they can be edited using tools common in many image processing software packages. In most cases, visually editing a classified map will improve the accuracy of the final product.

2.4.3. Other methods of classification in vogue

A wide variety of methods exist to derive measures of vegetation cover from remotely sensed data. These methods range widely in complexity, sophistication, and accuracy. The discrepancies are important for researchers to consider when incorporating or generating vegetation data for larger studies. Since the accuracy disparity between techniques is well documented, it should concern researchers who rely on simple linear vegetation indexes for accurate vegetation cover estimates. It is important to determine precisely how different the vegetation measurements will be between a simple, easy method, as compared to a more sophisticated, yet perhaps less accessible one.

Arguably the most widely used of these techniques is the Normalized Difference Vegetation Index (NDVI), It is a simple operation, needing little time, expertise, or processing capacity, which uses two bands of data to generate an index of relative vegetation abundance. Spectral Mixture Analysis (SMA) is a more sophisticated approach, using all bands of data in an image to generate percent cover of various specified ground covers within each pixel. Unfortunately field data was not available to assess the absolute accuracy of either of these techniques. However, a good evaluation is possible based on data comparisons, detailed image interpretation, reviews of possible error sources, and reviews of the wealth of literature on both these techniques.

2.4.3.1. Normalized Difference Vegetation Index

The dominant method for identifying vegetation using remotely sensed data is through vegetation indexes. Vegetation indexes are algorithms aimed at simplifying data from multiple reflectance bands to a single value correlating to physical vegetation parameters (such as biomass, productivity, leaf area index, or percent vegetation ground cover) (Tucker, 1979). These vegetation indexes are based on the well-documented unique spectral characteristics of healthy green vegetation over the visible to infrared wavelengths.

Healthy green vegetation generally reflects very little solar energy in the visible wavelengths (0.4-0.7 µm), with a sharp increase in reflectance in the near-infrared wavelength region (0.7-1.1 µm), This "red edge" is unique to vegetation as a surface material. Dead or senescent vegetation and soil generally reflect relatively greater amounts of energy in the visible wavelengths and less in the near-infrared. This unique spectral property of green vegetation is used in various indexes ranging in complexity from applying correlation coefficients to brightness values of a near-infrared band, to multi-band ratioing combined with complex algorithms. Arguably the most successful and commonly used of these techniques is the Normalized Difference Vegetation Index (NDVI).

NDVI is the traditional vegetation index used by researchers for extracting vegetation abundance from remotely sensed data (Tucker, 1979). It divides the difference between reflectance values in the visible red and near-infrared wavelengths by the overall reflectance in those wavelengths to give an estimate of green vegetation abundance (Tucker, 1979). In essence, the algorithm isolates the dramatic increase in reflectance over the visible red to near infrared wavelengths, and normalizes it by dividing by the overall brightness of each pixel in those wavelengths. Specifically NDVI is:

$$NDVI = IR\text{-}Red / IR\text{+}Red$$

where the values in either band have been converted from raw DN values to radiance of solar electromagnetic radiation, The result of this algorithm is a single band data set, ranging from -1 to 1, with values corresponding to photosynthetic vegetation abundance. NDVI has been used extensively to measure vegetation cover characteristics on a broad-scale worldwide, and has been incorporated into many large-scale forest and crop assessment studies (Peterson *et al.*, 1987; Asrar *et al.*, 1984), It is used to provide weekly vegetation maps, monitor crops over large regions, monitor vegetation change in much of the tropics, and estimate biomass.

Despite this wide use, some well-documented accuracy limitations exist. The limitations of vegetation indexes emanate from the fact that relationships between vegetation abundance and electromagnetic reflectance values in complex vegetation structures (and areas with high vegetation abundance) are many times nonlinear, whereas vegetation indexes are simple linear algorithms. Therefore, because of increased mutual shadowing in mature stands, aging forests may show a decrease in NDVI while actual biomass increases. Consequently, once vegetation indexes reach a threshold level they no longer accurately correlate to actual vegetation abundance (Wiegand *et al.*, 1991),

Studies have also shown that background soil color affects NDVI, especially in heterogeneous scenes (Huete, 1988). Because the difference between the bands is divided by the overall brightness of the two bands, extreme variations in background soil brightness can cause NDVI values to be artificially high or low. In theory, pixels with dark soil backgrounds, such as the basaltic soil patches, have a lower overall brightness. Therefore NDVI values would be artificially higher in these areas, as the difference between the visible and near infrared would be divided by less. Similarly, bright soil backgrounds would raise the overall brightness levels and therefore vegetation values derived through NDVI would be artificially lower than areas with similar abundance that have dark soil backgrounds. This background soil effect is additionally complicated by multiple scattering effects between vegetation and soil (Huete, 1988).

While NDVI has been shown to correlate reasonably well in medium to low vegetation abundance with various ecological parameters (such as leaf area index or green leaf biomass) (Anderson *et al.*, 1993), the literature suggests that in certain environments specific types of changes in vegetation may not be accurately depicted by NDVI (Asrar, 1984; Peterson *et al.*, 1987).

2.4.3.2. Spectral Mixture Analysis

Many other means of quantifying vegetation cover from remotely sensed data have been developed. One of the most promising is Spectral Mixture Analysis (SMA), a more sophisticated technique that utilizes all available bands of data to separate each pixel into fractions of specified land covers (Huete, 1986). The conceptual model used to develop SMA is that most pixels in scenes are mixtures of a few specific ground covers (or endmembers), especially in arid areas and mixed land use environments. If pure spectra of spectrally distinct primary land cover materials (i.e., vegetation, water and soil) in a scene can be found, a data set can be converted to fractions of each pre-defined land cover for each pixel (Adams *et al.*, 1995; Huete, 1986).

Linear mixture modeling assumes that endmembers (pre-defined primary land covers) are arranged in spatially distinct areas in each pixel and can therefore be extracted through the application of specific algorithms. Each pixel is modeled as a spatial mixture of endmember spectra to determine the physical abundance of land cover types in each pixel area.

The results of SMA are the percent coverage of each defined ground cover material, or endmember, in each pixel. This method had the advantage of deriving not only vegetation data, but land cover fractions for all the endmembers used, as well. Additionally, the data is generated into a physically-based measure, and therefore easily integrated into studies as measures of percent live cover rather than an indexed, relative measure. Elmore *et al.*, 2000 found percent live cover estimates using Spectral Mixture Modeling to be accurate within 4.0% and change in percent live cover to have a precision of 3.8%, Specific examples of research using SMA include monitoring rural land use changes and their effects on soil characteristics in Europe (Sommer *et al.*, 1998), estimating erosion (Metternicht & Fermont, 1998).

Despite the utility and accuracy of this method, limitations to SMA exist. In addition to being limited in the total number of possible endmembers. SMA is limited by the type of endmembers that can be used, especially when using multispectral data (Adams, *et al.*, 1995; Roberts *et al.*, 1993). Endmembers must be spectrally distinct from one another and generally account for the dominant land cover and spectral characteristics of the scene. Therefore, without hyperspectral data, it is virtually impossible to use this method to generate fractions of different types of photosynthetic vegetation. Generally researchers are limited to vegetation, soil, sand, and shade when using multispectral satellite imagery. Additionally, this process requires a good deal of processing capabilities and expertise in order to find pure spectra of appropriate endmembers in the scene. However, it is important to emphasize the advantage of additional datasets of endmember surface cover that are generated using SMA, as these can be used to extract more information from scenes than vegetation index information alone.

2.5. Ground Data Collection

Although land cover maps are often made without visiting the field, there are good reasons why field visits should be made. The two primary reasons for visiting the area that is being mapped are to collect data that can be used to train the algorithm or the interpreter and to collect data that can be used to evaluate the land cover map and estimate the accuracy of the individual classes (a process called validation). At a minimum, these data can be collected in one trip but often two or more trips are preferred so that validation information can be systematically collected using a sampling design based on the classification results.

Data collected in the field must be geo-referenced so that the point where the data were collected can be located on the imagery. GPS receivers are commonly used to record this location information. The type of information collected can range from detailed notes describing a site to a photograph of the site. Some of the detailed information that can be recorded includes: type of vegetation, crown closure, slope, aspect, soil type, and other bio-physical characteristics that are important to identify the land cover type. If photographs are taken it is a good idea to record the direction the camera was pointed and to make notes about the area to supplement the content in the photograph. For example, you could add information about species composition, tree height, and possibly land use.

When land cover maps are created without using field data from the region of interest it is difficult to predict the accuracy of the final land cover map. An analyst with significant experience may be able to produce a land cover map of high quality but without validation information the true accuracy of the image classification quality is not known.

2.6. Accuracy Assessment

No land cover classification project would be complete without an accuracy assessment. It may well be noted 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 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 versus 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.,* 2000). 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. 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-derive proportions of land cover types, with 200 samples at the first stage and only 25 among these described in the field. To complicate 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 labelling, 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).

2.7. Land Use Land Cover Mapping - Issues

Since land cover changes over time, the temporal resolution is a critical consideration in choosing the appropriate data type. Figure 2.4 portrays the relationships between spatial resolution, temporal resolution and satellite data sources. The dotted 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 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 in the figure represents mapping with frequently obtained coarse resolution data. With such data 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, along with 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., Cihlar and Beaubien, 1998, DeFries *et al.,* 1998, Hansen *et al.,* 2000). 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. So far, satellite-based large-area mapping has been mostly performed in region A because of the availability of data and the manageable computational demands. Land cover maps at 8 km resolution or coarser were prepared from AVHRR Global Area Coverage (GAC) data (DeFries and Townshend 1994, DeFries *et al.*, 1998). Maps for landscape regions (e.g., Cihlar *et al.*, 1997a,b, Steayert *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 , intensive activities led to global products at the same resolution (Loveland and Belward, 1997, Hansen *et al.* 2000, Loveland *et al.*, 2000). So far, region A maps have been

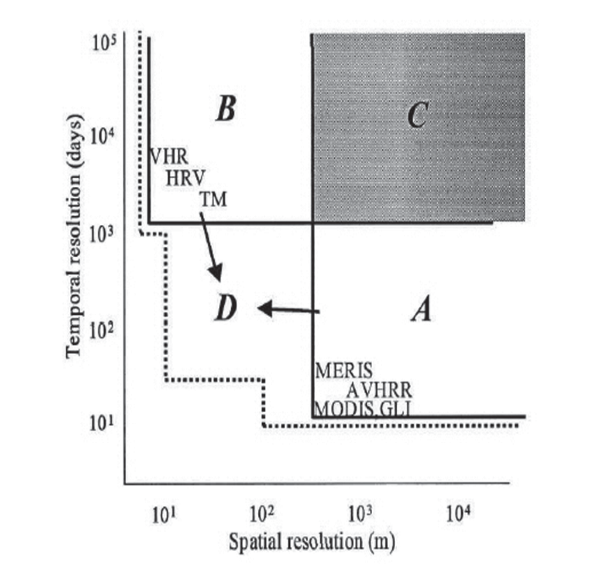

Figure 2.4: Land Cover Mapping requirements expressed in spatial and temporal resolutions. The acronomy represents satellite sensors at both fine and coarse resolutions; VHR – very high resolution sensors (Source: Cihlar,2000)

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), humid tropical deforestation studies, and other experimental products prepared through scene compositing (Guindon 1995, Homer *et al.*,1997, Beaubien *et al.*, 1999, Vogelmann *et al.*, 1998). Apart from some methodological studies (e.g., Moody and Woodcock, 1996, Cihlar *et al.*, 1998e), little work on region D has been carried out.

2.8. Research needs and Opportunities

In general, research needs and opportunities are related to 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.

2.8.1. Pre-processing

Assuming that the range of land cover mapping requirements is represented by all four areas A–D, 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 pre-processing 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 pre-processing 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 pre-processing stage, they must be dealt with during classification.

2.8.2. Classification

Cihlar *et al.,*(1998e) 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 a few classes (e.g., Iverson *et al.,*1994, Zhu and Evans 1994, DeFries *et al.,*1997) needs to be extended to multiple cover types.

Although for scene composites (Region B, figure 2.4) 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 2.4. Region D is the most demanding, with high spatial and temporal resolutions. It is also an area where large progress can be expected.

2.9. Land Use Land Cover Change

Changes in land use and land cover impact both environmental quality and the quality of life, two aspects that impact human wellbeing. Changes in habitat, water and air quality and the quality of life are some of the environmental, social and economic concerns associated with land use and land cover changes.

Habitat: Land use by human leads to changes in land cover that can negatively impact biodiversity. Conversion of natural wood- and grass-lands to more developed uses decreases the amount of habitat available. The pattern of human land use also tends to result in a patchy landscape, fragmenting habitats. Some species of plants and animals do better in patchy, fragmented environments, while others need large, uninterrupted areas.

Water Quality: Changes in land use can affect the volume, timing and quality of runoff water. More-developed land uses have higher proportion of impervious surface (areas where water can not soak into the ground, such as roadways, parking lots, and building roofs). As the amount of impervious surface increases, rainstorm runoff increases in volume, increasing the risk of flooding and increasing the amount of pollutants carried into streams and lakes. Human use of land also disturbs natural land cover, increasing the potential for soil erosion into streams and lakes.

Quality of Life (aesthetics, recreation, congestion): Land use and land cover changes can affect quality of life when those changes impact landscapes that have aesthetic value (scenic views), or when the quality and quantity of the landscapes are reduced in areas that are attractive for recreational activities. Also, changes in Land Use and Land Cover can affect traffic patterns that can have positive or negative effects on congestion.

Air Quality: The pattern of land use in a region can affect its air quality. If residential areas are located far from shopping and work centers, automobile use and emissions will be higher. If forests or other natural areas that purify air are developed, local air quality can worsen. Changes in vegetative cover can also lead to local changes in climate.

Global Carbon Cycles: More-natural landscapes can capture and store carbon in the soil, decreasing the amount of carbon dioxide in the atmosphere. If vegetation is cut and/or the soil is disturbed, stored soil carbon can be released back into the atmosphere. Several studies have examined the social and economic factors that drive Land Use and Land Cover change. These include:

Population Growth or Decline: As a region's population grows, the new residents need housing, as well as places to work and shop. In a region with declining population, there will be less new construction of homes and businesses.

Economic Growth: A booming regional economy will result in construction of new commercial and industrial buildings to house that activity. As the economy grows, the new jobs created will attract workers, leading to population growth, leading to construction of new homes and places to shop. As incomes rise, household may choose to build new larger homes on larger lots, leaving smaller, older houses vacant.

Demographics: The average number of people living in a household has been decreasing over time. Therefore, more housing units are needed to house the same number of people. The number of retired households is increasing, and these households tend to have few members. Meanwhile, the proportion of non-white households is also increasing, These households tend to have more members on average than white households.

Agricultural and forest products: A change in the price of agricultural or forest products can affect landowners' decisions whether to keep the land in those uses. Policies aimed at supporting agricultural prices provide an incentive to keep land in farming.

Regional and local planning and policies: Regions can influence the rate at which land use and land cover change through a variety of means.

2.9.1. Land Use & Land Cover Change Detection with Remote Sensing data

An increasingly common application of remotely sensed data is for change detection. Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times (Singh, 1989). Change detection is an important process in monitoring and managing natural resources and urban development because it provides quantitative analysis of the spatial distribution of the population of interest. Change detection is useful in such diverse applications as land use change analysis, monitoring shifting cultivation, assessment of deforestation, study of changes in vegetation phenology, seasonal changes in pasture production, damage assessment, crop stress detection, disaster monitoring, day/night analysis of thermal characteristics as well as other environmental changes (Singh, 1989).

Macleod and Congalton (1998) list four aspects of change detection which are important when monitoring natural resources:

- Detecting that changes have occurred
- Identifying the nature of the change
- Measuring the areal extent of the change
- Assessing the spatial pattern of the change

The basic premise in using remote sensing data for change detection is that changes in land cover result in changes in radiance values which can be remotely sensed. Techniques to perform change detection with satellite imagery have become numerous as a result of increasing versatility in manipulating digital data and increasing computing power.

A wide variety of digital change detection techniques have been developed over the last two decades. Singh (1989) and Coppin & Bauer (1996) both provide excellent and comprehensive summaries of methods and techniques of digital change detection. Coppin & Bauer (1996) summarize eleven different change detection algorithms that were found to be documented in the literature. These include:

- monotemporal change delineation
- delta or post-classification comparison
- multidimensional temporal feature space analysis
- composite analysis
- image differencing
- image ratioing
- multitemporal linear data transformation
- change vector analysis
- image regression
- multitemporal biomass index
- background subtraction

The scientific literature reveals that digital change detection is a difficult task to perform accurately and unfortunately, many of the studies concerned with comparative evaluation of these applications have not supported their conclusions by quantitative analysis (Singh, 1989). Digital change detection is affected by spatial, spectral, temporal, and thematic constraints. The type of method implemented can profoundly affect the qualitative and quantitative estimates of the change. Even in the same environment, different approaches may yield different change maps. The selection of the appropriate method therefore takes on considerable significance. Not all detectable changes, however, are equally important to the resource manager. On the other hand, it is also probable that some changes of interest will not be captured very well, or at all by any given system. Figure 2.5 illustrates LULC change detection capabilities of satellite data.

According to recent research by Coppin & Bauer (1996), image differencing appear to perform generally better than other method of change detection; and such monitoring techniques based on multispectral satellite data have demonstrated potential as a means to detect, identify, and map changes in forest cover. Image differencing is probably the most widely applied change detection algorithm for a variety of geographical environments (Singh, 1989). It involves subtracting one date of imagery from a second date that has been precisely registered to the first.

The vegetation index (VI) differencing is one of the most popular change detection algorithms. The fundamentals for this technique rely on the idea that if VIs are correlated to biomass, then the decrease of vegetation can be detected by a difference of VI images (one before and other after the land cover change). In this method, the first step is to calculate a differencing image by subtracting two coregistered images, followed by the application of a threshold to distinguish significant spectral differences as areas of land cover change. Four types of VI can be tested: (1) Normalised Difference Vegetation Index (NDVI) one of the most common indices used in remote sensing studies, (2) the Atmospherically Resistant Vegetation Index (ARVI), which accounts for the atmospheric influence in the sensor output, (3) the Soil Adjusted Vegetation Index (SAVI) (Huete, 1988) that accounts for the background effect, and (4) the Modified Soil Adjusted Vegetation Index (MSAVI2), which is an improvement of SAVI. Change Vector Analysis (CVA) is another well-accepted change detection technique. The change vector of a pixel is defined as the vector difference between the multi-band digital vectors of the pixel on two different dates. When a forest suffers a change, its spectral characteristics also change. The vector describing this change is known as the pixel change vector and describes the intensity and the direction of the change that occurred between the first and the second date. The CVA is applied to two co-registered bands of an image, in two different dates. With this method, two images are computed: one image for the vector intensity and another for the vector direction. The first image contains the information of change, while the second contains information on the type of change. CVA can be applied to two different spectral data sets: original TM bands and the components of the Tasseled Cap transformation, brightness (B), greenness (G) and wetness (W).

Principal Components Analysis (PCA) is another technique available. PCA is one of the most popular multivariate analysis techniques for data reduction. The PCA transformation leads to the description of multidimensional data in which axis variables are uncorrelated. In the transformed data, the first variable or component (PC1) contains the higher variance present in the data while the subsequent variables contain decreasing proportions of data scatter. Experiments have shown that the first components contain the unchanged spectral information, while the changed information is contained in the latter components (Byrne et al., 1980). PCA can be performed on original or standardised data, The former uses the covariance matrix, and the latter uses the correlation matrix.

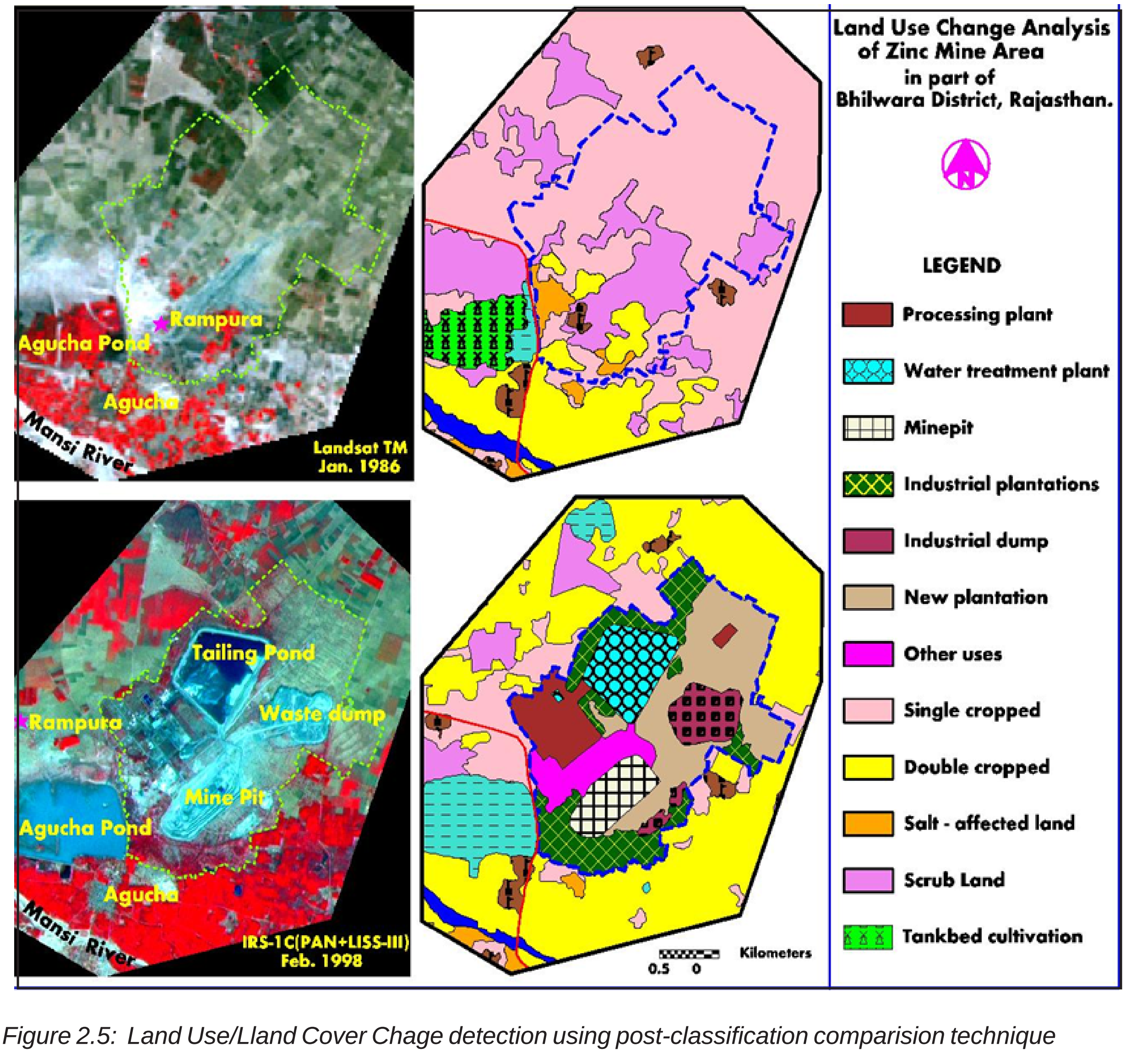

Figure 2.5: Land Use/Lland Cover Chage detection using post-classification comparision technique

2.10. Land Use Modeling

Land is a dynamic canvas through which human and natural systems interact. Understanding the many factors influencing Land Use Cover Change (LUCC) has been the focus of scientific study across multiple disciplines, locations, and scales. But direct measurements alone are not sufficient to provide an understanding of the forces driving change. Linking observations at a range of spatial and temporal scales to empirical models provides a comprehensive approach to understanding land-cover change (Turner *et al.*,1994).

The primary utility of models is to provide a systematic approach to understanding a research problem. An important aspect is the link between direct observations, case studies, and models in an effort to test or identify dominant features of land-cover change. Development of diagnostic models can lead to an improved understanding of the current and recent situation and at the same time provide credible, geographically-referenced predictions. The length of time over which a prediction is valid is a function of the persistence of the observed phenomena. There is evidence to suggest that much, if not most, land-cover change is spatially and temporally persistent over 10 to 15 year intervals. It should be noted, however, that certain events can alter trends significantly and rapidly. Changes in political, institutional, and economic conditions can cause rapid changes in the rate or direction of land-cover change. Therefore, an effort to understand the primary kinds of influences which cause land-cover change trends to diverge rapidly is also an important component of this programme.

Several different approaches are used to project future Land Use and/or Land Cover. These can be divided into two broad categories: a) models that predict total land use change for a region, and b) models that predict Land Use for specific parcels or grid cells. If the analyst wants to know the total amount of land use change that will occur in a large region like a state, then the first type of model is appropriate. On the other hand, if the analyst wants to know where in the region land use change will occur, or to project what will happen at a specific place, then the second type of model is appropriate.

The goal of this discussion is to provide a broad overview of these models, offer our perspective on their potential role in LUCC modeling, discuss some key issues related to their development and implementation, and briefly review ongoing research based on this modeling paradigm.

2.10.1. Approaches to Modeling Land-Use/Cover Change

The strengths and weaknesses of seven broad, partly overlapping, categories of models: mathematical equation-based, system dynamics, statistical, expert system, evolutionary, cellular, and hybrid are discussed for comparison. This review is not exhaustive and only serves to highlight ways in which present techniques are complemented by those models that combine cellular and agent-based models. More comprehencive overview of LUCC Modeling techniques is given by Agarwal, 2000.

Equation-Based Models

Most models are in some way mathematical, but some are especially so in that they rely on equations that seek a static or equilibrium solution. The most common mathematical models are sets of equations based on theories of population growth and diffusion that specify cumulative land-use/cover change over time (Sklar and Costanza, 1991). A variant of this model is based on linear programming (Howitt, 1995), potentially linked to GIS information on land parcels (Cromley and Hanink, 1999). A major drawback of such models is that a numerical or analytical solution to the system of equations must be obtained, limiting the level of complexity that may practically be built into such models.

System Models

System models represent stocks and flows of information, material, or energy as sets of differential equations linked through intermediary functions and data structures. Time is broken into discrete steps to allow feedback. Human and ecological interactions can be represented within these models, but they are dependent on explicit enumeration of causes and functional representation, and they accommodate spatial relationships with difficulty (Sklar and Costanza, 1991).

Statistical Techniques

Statistical techniques are a common approach to modeling land-use/cover change, given their power, wide acceptance, and relative ease of use. They include a variety of regression techniques applied to space and more tailored spatial statistical methods . Unless they are tied to a theoretical framework, statistical techniques may downplay decision making and social phenomena such as institutions. Successful examples of combining theory and statistics are provided by spatial econometrics (Leggett and Bockstael, 2000).

Expert Models

Expert models combine expert judgment with nonfrequentist probability techniques such as Bayesian probability or Dempster-Schaefer theory or symbolic artificial intelligence approaches such as expert systems and rule-based knowledge systems (Lee *et al.*, 1992). These methods express qualitative knowledge in a quantitative fashion that enables the modeler to determine where given land uses are likely to occur. It can be difficult to include all aspects of the problem domain, however, which leaves room for gaps and inconsistencies.

Evolutionary Models

Within the field of artificial intelligence, symbolic approaches such as expert systems are complemented by a biologically inspired evolutionary paradigm. Exemplars of this field, such as artificial neural networks and evolutionary programming, are finding their way into LUCC models (e.g., Balling *et al.*,1999). In brief, neural networks are silicon analogs of neural structure that are trained to associate outcomes with stimuli. Evolutionary programming mimics the process of Darwinian evolution by breeding computational programs over many generations to create programs that become increasingly able to solve a particular problem.

Cellular Models

Cellular models (CM) include cellular automata (CA) and Markov models. Each of these models operates over a lattice of congruent cells. In CA, each cell exists in one of a finite set of states, and future states depend on transition rules based on a local spatiotemporal neighborhood. The system is homogeneous in the sense that the set of possible states is the same for each cell and the same transition rule applies to each cell. Time advances in discrete steps, and updates may be synchronous or asynchronous (Hegselmann 1998). In Markov models, cell states depend probabilistically on temporally lagged cell state values. Markov models may be combined with CA for LUCC modeling as evidenced by joint CA-Markov models (Balzter, Braun, and Kohler 1998). Global land-use/ cover change in response to climate change (Alcamo, 1994).

Cellular models have proven utility for modeling ecological aspects of land-use/cover change, but they face challenges when incorporating human decision making. It is necessary to use complex hierarchical rule sets to differentiate between the kinds of decision making that apply to groups of cells, such as local land tenure structure (e.g., Li, 2000). While effective, these deviations from generic cellular automata come at the potential cost of moving away from the advantages of the generic approach. In particular, “in order to converse with other disciplines, from biology and physics to chemistry, it may be necessary that the form of CA preserve as many features of strict and formal CA models as possible” (Torrens and O’Sullivan, 2001).

2.10.2. Hybrid Models

Hybrid models combine any of the above-mentioned techniques, each of which is a fairly discrete approach unto itself. A prime example is estuarine land-use/cover transition modeling that has an explicit, cellular model tied to a system dynamics model (Costanza, Sklar, and Day, 1986). Other examples that combine statistical techniques with cellular models and system models include larger-scale models such as CLUE family (Veldkamp and Fresco, 1996).

A distinct variant of hybrid models is dynamic spatial simulation (DSS), which portrays the landscape as a two-dimensional grid where rules represent the actions of land managers based on factors such as agricultural suitability (Lambin, 1994). Dynamic spatial simulation typically does not represent heterogeneous actors, institutional effects on decision making, or multiple production activities. However, due to their ability to represent individual decision making and temporal and spatial dynamics, they represent an important advance over previous models (Lambin, 1994).

2.10.3. Agent-Based Models

While cellular models are focused on landscapes and transitions, agent-based models focus on human actions. Agents are the crucial component in these models. Several characteristics define agents: they are autonomous, they share an environment through agent communication and interaction, and they make decisions that tie behavior to the environment. Agents have been used to represent a wide variety of entities, including atoms, biological cells, animals, people, and organizations (Conte *et al.*, 1997; Janssen & Jager, 2000).

One key difference exists between agent-based modeling and other techniques. Complex systems are often characterized by nonlinear relationships between constantly changing entities while systems theory typically studies static entities linked by linear relationships defined by flows and stocks of energy, information, or matter. Similarly, systems theory emphasizes quantities of flow and not necessarily their quality, while complexity research attempts to examine qualitative attributes such as learning and communication. Complex behavior is seen as emerging from interactions between system components while system models tend to favor parameterized flows and stocks that assume that the system exists in equilibrium due to fixed relationships between system elements. Agent-based modeling relies on the idea that emergent or synergistic characteristics are understood by examining subcomponent relationships.

2.10.3.1. Multi-Agent Systems (MAS) for Land-Use/Cover Change

The exploration of modeling thus far has raised three key points. First, of the host of methods used to model land-use/cover change, dynamic spatial simulation offers a promising degree of flexibility. Second, as noted above, cellular models successfully replicate aspects of ecological and biogeophysical phenomena, but they may not always be suited to modeling decision making. Third, agent-based modeling is a promising means of representing disaggregated decision making. When all three points are taken together, they suggest the use of a dynamic, spatial simulation-like MAS/LUCC model that consists of two components. The first is a cellular model that represents biogeophysical and ecological aspects of a modeled system. The second is an agent-based model to represent human decision making. The cellular model is part of the agents' environment, and the agents in turn act on the simulated environment. In this manner, the complex interactions among agents and between agents and their environment can be simulated in a manner that assumes equilibrium conditions. Rather, equilibria or transient but reoccurring patterns emerge through the simulated interactions between agents and their environment.

2.10.4. Current Applications of MAS/LUCC Modeling

Many well-developed techniques for modeling land-use/cover dynamics exist. However, each of these techniques has some limitations. Equation-based models may require simplifying assumptions to achieve analytical or computational tractability, and they are often based on empirically implausible assumptions regarding static market equilibria. System models directly address the shortcomings of equation-based models in terms of representing feedbacks and dynamic processes, but these models also operate at a very aggregated level, or, equivalently, at a very coarse temporal and spatial resolution. Therefore, where local heterogeneity and interactions are important, such models may have limited explanatory power.

Some insight into the impacts of spatial heterogeneity, neighborhood effects, and spatial spillovers can be gleaned through estimation of statistical models. However, these models distill information into parameter estimates that represent average effects over available data. Thus, such models may be useful for projecting spatial dynamics and interactions only for processes which are stationary and uniform over space and time. While the impacts of spatial influences occurring at hierarchical spatial scales can be represented to some extent through statistical techniques that account for regional heterogeneity (such as generalized least-squares, fixed-effect, and random-effect models), feedbacks across scales cannot be effectively modeled. While cellular modeling techniques offer greater flexibility for representing spatial and temporal dynamics, these dynamics also are based on stationary transition probabilities. Therefore, such models have limited ability to reflect feedbacks in the system under study, as global changes in the system do not influence transitions at the cellular level. Perhaps most significant, none of the above modeling techniques can represent the impacts of autonomous, heterogeneous, and decentralized human decision making on the landscape.

Many of these limitations are potentially overcome by MAS/LUCC models. In particular, MAS/LUCC models may be well suited for representing socioeconomic and biophysical complexity. They also might be well suited for the related goal of modeling interactions and feedbacks between socioeconomic and biophysical environments.

2.11. Land Use/Cover Change, Climate and Environment

2.11.1. Effect of land use/land cover on local climate

Land surface changes can affect local precipitation and temperatures. Vegetation patterns and soil composition can influence cloud formation and precipitation through their impact on evaporation and convection i.e., the rise of air, The effect of land cover on climate depends on the type of land cover that is present in a specific region. For example, barren lands tend to heat more rapidly and can transmit this heat to the lower atmosphere.

A recent study of the United States on summer climate using computer models of NASA and the National Oceanic and Atmospheric Administration found that land cover changes from grassland to agriculture in part of the Great Plains and the Midwest brought as a result a significant cooling effect. A possible explanation is that farmlands tend to create lower temperatures due to increase in evaporation. In the same study, a warming effect associated to land use change from forest to croplands was found along the Atlantic cost of the United States. Within the climate system, forests are more efficient in transpiration processes where the evaporation of plants during photosynthesis and helps to cool the air.

Land surface changes can affect local temperatures not only in forests or agricultural land but also in urban areas. For example, average temperatures in downtown areas of a city can increase due to the high density of construction materials such as pavements and roofs. Higher temperatures in urban areas compared to lower temperatures in surrounding rural areas, has been called by scientists the urban heat island effect.

2.11.2. Effect of land use/land cover on global climate

Every new building constructed consumes energy both in its construction and use. Single family homes use more energy per person than multifamily homes. Larger homes use more energy than smaller homes. The farther new homes are from existing population centers, from work and shopping, the greater the additional energy use in transportation per home and per person. Because of the strong links between energy use, greenhouse gas emissions and climate change, rates of new construction are strongly related to rates of climate change, especially when this new construction is relatively distant from existing population centers.

Moreover, the consequences of new construction for climate change go beyond their effects on Green House Gases (GHG) emission rates. Areas under forest, wetland, even agricultural fields serve as Carbon 'sinks'. That is, they absorb and retain Carbon from the atmosphere. New construction then not only increases rates of GHG emission, it reduces the amount of Carbon that is stored in areas with vegetative cover. There are differences in carbon storage of 'undeveloped' areas: forests store more carbon than farmland; different forest-types store different amounts of carbon; farming practices with minimal tillage and/or which include trees or perennials store more carbon than those with complete tillage and only annual row crops.

2.11.3. Impact of climate change on land use/land cover

The effect of climate's impact on land cover refers to the direct and indirect influence that climate has on the vegetation, or other features that cover the land (Ecosystems). Climate change produces alterations in water, energy and carbon fluxes. It also could also produce environmental disturbances that directly or indirectly affect land cover. For example, species respond to disturbances produced by climate change through migration, extinction or adaptation to new disturbances.

Most of the work that has looked at the impacts of climate change on Land Use has focused on agricultural land and forests. Variability in climate can affect agricultural land patterns due to a) rainfall patterns. b) temperatures (particularly night temperatures) and c) CO_2 enrichment. Controlled experiments have found that greater variability in rainfall patterns result in lower overall plant growth due to decreased water availability in the upper 30 cm of soil. Higher temperatures are likely to make growing seasons longer, allowing the possibility of more than one cropping cycle during the same season as well as the expansion of agricultural and forest land towards the poles and to higher elevations. At the same time, increases in night time temperatures can affect biological processes such as respiration and could result in reduction of potential yields.

Scientists are trying to understand the responses of CO_2 enrichment (higher volumes of CO_2 in the atmosphere) on different species. Wheat, rice and soybeans are crops that seem to have a positive response (increased overall observed growth) to higher CO_2 levels in the atmosphere. Crops such as corn are likely to be less responsive to CO_2 enrichment. Other potential impacts of climate change on land cover include: Natural fire frequency, intensity and duration and potential rise of sea level and floods, especially in coastal areas.

Given all the factors mentioned above, the net impact on agriculture in a particular area could be positive or negative. If climate change makes agriculture less productive in an area, then more farm land will be converted to other uses. If climate change offers more agricultural produce in an area, land that is currently in forests may be converted to agricultural uses.

Humans can also respond to climate change through migration. If warmer places are considered amenities to humans, population density can increase in areas with higher temperatures. The new population settlements indirectly affect land cover as more development and land fragmentation occurs. Proactive land use planning can be used to anticipate and adapt to Climate Change. The following are examples of potential strategies to minimize the potential negative impacts from climate change:

- One possible impact from climate change is an increase in severity of storms, which would lead to an increase in flash flooding. Adaptation strategies include banning new construction in vulnerable areas with high risk of flooding, minimizing flashy runoff from impervious surfaces, changing the requirements for stormwater retention structures in new developments, and protection of wetlands that buffer runoff from heavy rainstorms
- Increased temperatures will make urban heat effects more severe. Land use planning should reduce urban heat effects, through maintenance of green areas, use of different building materials
- The global climate in future is expected to become more variable. This will increase stress on natural ecosystems. Species that rely on natural, undisturbed habitat will have difficulty surviving droughts and storms, particularly if that habitat exists only in small patches. These habitats will be more resilient to climate variation if they are connected, so that populations can move and repopulate areas that are impacted by drought or severe storms. Land use planning can include provisions for habitat corridors that connect isolated patches of suitable habitat
- As sea levels rise, the shoreline along coastal areas will erode. Where there are beachfront or bayfront houses, the owners will try to protect their property, through shoreline hardening for example. It is much easier to adapt to sea level rise if those properties are not built to begin with. Land use policies that discourage shoreline building will leave communities more flexibility to deal with sea level rise
- Climate change will make some agricultural areas more suitable for production and other areas less so. The impacts of climate change on agriculture will be less if production is allowed to move in response to changing climate. Some land that is not currently suitable for agriculture because of climate may become suitable in the future. If that land is not available because it has already been developed, then the farming sector will be less able to adapt. It may make sense to preserve land for future agricultural production, even if it is not currently being used for that purpose. Similarly, forest land that is currently dominated by lower-valued species may become more valuable in the future, and vice versa.

2.12. Conclusions

Earth observations have the potential to respond to the growing and urgent demand for timely and accurate land cover information over large areas. In the recent past, land cover mapping from satellites has come of age, Through research on various issues regarding data pre-processing, classification and accuracy assessment, new and unique data / land cover products are being generated which could not be produced by earlier techniques. Many of the technical limitations hampering further improvements in land cover mapping need to 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. This will require strong, ongoing research activities as well as new initiatives in the production of land cover maps. The future research in LULC studies needs to address the best ways of taking advantage of satellite-derived land cover databases through LULC change modeling techniques which provide important inputs for studies in the emerging areas of environmental monitoring, global warming and climate change.

References

Adams JB, Sabol DE, Kapos V, Filho RA, Roberts DA , Smith MO and Gillespie AR, 1995, Classification of Multispectral Images based on Fractions of Endmembers: Application to land-cover change in the Brazilian Amazon, *Remote Sensing of the Environment,* **52** :137-154.

Agarwal C, Green GM, Grove JM , Evans T and Schweik C, 2000, A review and assessment of land-use change models: Dynamics of space, time, and human choice, Paper presented in the Fourth International Conference on Integrating GIS and Environmental Modeling (GIS/EM4), September 2–8, Banff, Canada.

Ahern FJ, Janetos AC and Langham E, 1998, Global Observation of Forest Cover: a CEOS' Integrated Observing Strategy, Proceedings of 27th International Symposium on Remote Sensing of Environment,Troms,Norway, p. 103–105.

Alcamo J, 1994, *IMAGE 2.0: Integrated Modeling of Global Climate Change*, Kluwer Academic Publishers, Dordrecht, Germany.

Anderson GL, Hanson JD and Haas RH,1993, Evaluating landsat thematic mapper derived vegetation indices for estimating above–ground biomass on semiarid rangelands, *Remote Sensing of Environment*, **45**: 165–175.

Anderson JR, Hardy EE , Roach JT and Witmer RE, 1976: A land use and land cover classification system for use with remote sensor data, US Geological Survey Professional Paper 964, 28 pp.

Asrar G, Fuchs M, Kanemasu ET and Hatfield JL, 1984, Estimating absorbed photosynthetic radiation and leaf area index from spectral reflectance in wheat, *Agronomy Journal,* **76**: 300-306.

Atzberger CG, 1996, The spectral correlation concept: an effective new image-based atmospheric correction methodology over land areas, In Progress in *Environmental Remote Sensing Research and Applications*, edited by Parlow A (Rotterdam: Balkema), 125–132.

Balling RJ, Taber JT, Brown M and Day K, 1999, Multi-objective urban planning using a genetic algorithm, *ASCE Journal of Urban Planning and Development,* **125 (2)** : 86-99.

Balzter, H, P W Braun and W Kohler, 1998, Cellular automata models for vegetation dynamics, *Ecological Modelling,* **107 (2/3)**: 113-125.

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

Brown JF, Loveland TR, Merchant J W, Reed BC and Ohlen, DO, 1993, Using multisource data in global land cover characterization: concepts, requirements and methods, *Photogrammetric Engineering and Remote Sensing*, **59**: 977–987.

Burk TE, Ek AR, Coppin PR, Lime SD, Walsh TA, Walters DK, Befort W and Heinzen DH, 1994, Satellite inventory of Minnesota forest resources, *Photogrammetric Engineering and Remote Sensing*, **60**: 287–298.

Carpenter GA, Gjaja MN, Gopal S and Woodcock CE, 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.

Chuvieco E and Congalton RG,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, 2000, Land cover mapping of large areas from satellites: status and research priorities, *International Journal of Remote Sensing,* **21(6-7)**: 1093-1114.

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

Cihlar J, Latifovic R, Chen J and Li Z, 1999, Near-real time detection of contaminated pixels in AVHRR composites, *Canadian Journal of Remote Sensing,* **25**: 160–170.

Cihlar J, Ly H and Xiao Q, 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, 1998, Classification by Progressive Generalization: a new automated methodology for remote sensing multichannel data, *International Journal of Remote Sensing*, **19**: 2685–2704.

Colwell RN, (editor) 1960, *Manual for Photographic Interpretation*, The American Society of Photogrammetry, Washington, D.C.

Congalton RG, 1991, A review of assessing the accuracy of classifications of remotely sensed data, *Remote Sensing of Environment,* **37**: 35–46.

Congalton RG, 1996, Accuracy assessment: a critical component of land cover mapping, In Gap Analysis: A Landscape Approach to Biodiversity Planning, edited by Scott JM, Tear THandDavis F (Bethesda, Maryland: *American Society for Photogrammetry and Remote Sensing*), 119–131.

Conte R, Hegselmann R and Terna P, eds., 1997, *Simulating Social Phenomena*, Springer, Berlin.

Coppin, Pol R and Marvin E Bauer, 1996, Digital Change Detection in Forest Ecosystems, *Remote Sensing Reviews*,13207-234.

Costanza R, Sklar FH and JDay W Jr., 1986, Modeling spatial and temporal succession in the Atchafalaya/Terrebonne Marsh/estuarine complex in South Louisiana, P, 387-404 in D, A, Wolfe, ed, *Estuarine Variability*, Academic Press.

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

Cromley RG and Hanink DM, 1999, Coupling land-use allocation models with raster GIS, *Journal of Geographic Systems,* **1**: 137-153.

De Boissezon H, Gonzales G, Pus B and Sharman M, 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 RS, Hansen M and Townshend JRG, 1995, Global discrimination of land cover types from metrics derived from AVHRR Pathfinder data, *Remote Sensing of Environment*, **54**: 209–222.

DeFries R S, Hansen M, Townshend JRG and Sohlberg R, 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 of Remote Sensing,* **19**: 3141–3168.

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

DeFries RS and Townshend JRG, 1994, NDVI-derived land cover classification at global scales, *International Journal of Remote Sensing*, **15**: 3567–3586.

DeFries RS, Bounoua L and Collatz GJ, 2002, Human modification of the landscape and surface climate in the next fifty years, *Global Change Biology*, **8**: 438-458.

Dickinson RE, Henderson-Sellers A, Kennedy PJ and Wilson MF, 1986, Biosphere-atmosphere transfer scheme (BATS) for the NCAR community climate model, NCAR Technical Note NCAR/TN275+STR, Boulder, CO, USA.

Elmore, Andrew J, Mustard, John F, Manning, Sara J, Lobell and David B, 2000, Quantifying Vegetation Change in Semi-Arid Environments: Precision and Accuracy of Spectral Mixture Analysis and the Normalized Difference Vegetation Index, *Remote Sensing of the Environment*, **73(1)**: 87 - 102.

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

Eva HD, Malingreau JP, Gregoire JM, Belward AS and Mutlow CT, 1998, The advance of burnt areas in Central Africa as detected by ATSR-1, *International Journal of Remote Sensing,* **19**: 1635–1637.

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

Foody GM, Lucas RM, Curran PJ and Honzak M, 1997, Non-linear mixture modeling without end-members using an artificial neural network, *International Journal of Remote Sensing,* **18**: 937–953.

Friedmann DE, 1981, Operational resampling for correcting images to a geocoded format, Proceedings of the Fifteenth International Symposium Remote Sensing of Environment, Ann Arbor, MI (Environmental Research Institute of Michigan), 195–199.

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

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

Guindon B, 1995, Utilization of Landsat Pathfinder data for the creation of large area mosaics, Proceedings of the 1995 ACSM/ASPRS Conference, Charlotte, NC (*American Society of Photogrammetry and Remote Sensing*), **2**: 144–153.

Hammond TO and Verbyla DL, 1996, Optimistic bias in classification accuracy assessment, *International Journal of Remote Sensing*, **17:** 1261-1266.

Hansen MC, DeFries RS, Townshend, JRG and Sohlberg R, 2000, Global land cover classification at 1 km spatial resolution using a classification tree approach, *International Journal of Remote Sensing*, **21**: 1331–1364.

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

HolbenB, 1986, Characteristics of maximum-value composite images from temporal AVHRR data, *International Journal of Remote Sensing*, **7**: 1417–1434.

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

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

Houghton RA , 1999, The annual net flux of carbon to the atmosphere from changes in land use 1850-1990, *Tellus Series B-Chemical And Physical Meteorology*, **51**: 298-313.

Howitt RE, 1995, Positive mathematical programming, *American Journal of Agricultural Economics,* **77 (2)**: 329-42.

Huete AR,1986, Separation of Soil-plant Spectral Mixtures by Factor Analysis, *Remote Sensing of the Environment*, **19**: 237 - 251.

Huete AR, 1988, A soil-adjusted vegetation index (SAVI), *Remote Sensensing of Environment,* **25**: 295-309.

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

Intergovernmental Panel on Climate Change (IPCC), 2000, *Land use, Land-use Change, and Forestry: A Special Report*, R Watson *et al.* (Eds.), Cambridge University Press, Cambridge, U.K.

Iverson LR, Cook EA and Graham RL, 1994, Regional forest cover estimation via remote sensing: the calibration center concept, *Landscape Ecology,* **9**: 159–174.

Janetos AC and Justice CO, 2000, Land cover and global productivity: a measurement strategy for the NASA programme, *International Journal of Remote Sensing,* **21**: 1491-1512.

Janssen M A and Jager W, 2000, The human actor in ecological economic models, *Ecological Economics,* **35 (3)**: 307-310.

Kalkhan M A, Reich RM and Stohlgren TJ, 1998, Assessing the accuracy of Landsat Thematic Mapper classification using double sampling, *International Journal of Remote Sensing*, **19**: 2049–2060.

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

Lambin EF, 1994, *Modelling Deforestation Processes: A Review*, European Commission, Luxemburg.

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

Lark RM, 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.

Lee RG, Flamm R, Turner MG, Bledsoe C , Chandler P, DeFerrari C ,Gottfried R , Naiman RJ ,Schumaker N and Wear D, 1992, Integrating sustainable development and environmental vitality: A landscape ecology approach, pp 499-521 in R J Naiman, ed. *Watershed Management: Balancing sustainability and environmental change*, Springer-Verlag, New York.

Leggett CG and Bockstael NE, 2000, Evidence of the effects of water quality on residential land prices, *Journal of Environmental Economics and Management*, **39**: 121-144.

Li BL, 2000, Fractal geometry applications in description and analysis of patch patterns and patch dynamics, *Ecological Modelling,* **132 (1 / 2)**: 33-50.

Lillesand TM, 1996, A protocol for satellite-based land cover classification in the Upper Midwest, In Gap Analysis: A Landscape Approach to Biodiversity Planning, edited by Scott JM, Tear TH and Davis F(Bethesda, Maryland: *American Society for Photogrammetry and Remote Sensing*), 103–118.

Liu J, Chen JM, 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 TR and Belward AS, 1997, The IGBP-DIS global 1 km land cover dataset, DISCover: first results, *International Journal of Remote Sensing*, **18**: 3289–3295.

Loveland TR, Merchant JW, Brown JF, Ohlen DO, Reed BC, Olson P and Hutchinson J, 1995, Seasonal land-cover regions of the United States, *Annals of the Association of American Geographers*, **85**: 339–355.

Loveland TR, Merchant JW, Ohlen DO and Brown JF, 1991, Development of a land-cover characteristics database for the conterminous U.S., *Photogrammetric Engineering and Remote Sensing*, **57**: 1453–1463.

Loveland TR, Reed BC, Brown JF, Ohlen DO, Zhu Z, Yang L and Merchant JW, 2000, Development of a global land cover characteristics database and IGBP DISCover from 1-km AVHRR data, *International Journal of Remote Sensing*, **21** : 1303–1330.

Macleod RD and Congalton RG, 1998, *Photogrammatry Engineering and Remote Sensing*, **64**: 207–216.

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

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

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

Mertens B and Lambin EF, 1997, Spatial modelling of deforestation in southern Cameroon, *Applied Geography,* **17 (2)**: 143-162.

Metternich GI and Fermont A, 1998, Estimating erosion surface features by linear mixture modeling, *Remote Sensing of the Environment,* **64(3)**: 254-265.

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

National Remote Sensing Agency, 2004, Manual on National Land use /land Cover mapping on 1:250,000 scale using multi-temporal IRS P6-AWiFS data, NRSA, Dept. of Space, Govt. of India, Balanagar, Hyderabad.

Peterson DL, Spanner MA, Running SW and Tenber KB,1987, Relationship of Thematic Mapper Simulator data to Leaf Area, *Ecology* , **67 (1)**: 1273-1276.

Rabben EL, 1960, Fundamentals of photo interpretation, In Manual of Photographic Interpretation, edited by R N Colwell (Washington, DC: *The American Society of Photogrammetry*), 99–168.

Roberts DA, Smith MO and Adams JB, 1993, Green Vegetation, Nonphotosynthetic Vegetation, and soils in AVIRIS Data, *Remote Sensing of Environment,* **44(2-3)**: 255-269.

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

Rosenzweig C and Hillel D,1998, Climate Change and the Global Harvest: Potential Impacts of the Greenhouse Effect on Agriculture, *Journal of Agricultural and Environmental Ethics*, **11 (1)**: 71-74.

Running SW, Justice CO, Salomonson V, Hall D, Barker J, Kaufmann YJ, Strahler A H, Huette A R, Muller JP, Vanderbilt V, Wan ZM, Teillet P and Carneggie D, 1994, Terrestrial remote sensing science and algorithms planned for EOS/MODIS, *International Journal of Remote Sensing,* **15**: 3587–3620.

Running SW, Loveland TR, Pierce LL, Nemani RR and Hunt ER Jr., 1995, A remote sensing based vegetation classification logic for global land cover analysis, *Remote Sensing of Environment*, **51**: 39–48.

Schott JR, Salvaggio C and Volchok WJ, 1988, Radiometric scene normalization using pseudoinvariant features, *Remote Sensing of Environment*, **26**: 1–16.

Sellers PJ, Los SO, Tucker CJ, Justice CO, Dazlich DA, Collatz J A and Randall DA, 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.

Shimabukuro YE, Mello EM K, Moreira JC and Duarte V, 1997, Segmentacao e classi, cacao da imagemsombra do modelo demistura paramapear des• orestamento na Amazona, Report INPE-6147-PUD/029, InstitutoNacional de Pesquisas Espacias, Sao Jose dos Campos, Brazil.

Singh HC,1989, Rural Environment Development and Planning, Chugh Publications, Allahabad, India.

Sklar FH and Costanza R, 1991, The development of dynamic spatial models for landscape ecology: A review and prognosis: in M G Tuner and R H Gardner, eds, *Quantitative Methods in Landscape Ecology*, Springer-Verlag, New York, 239-288.

Sommer S, Hill J and Megier J,1998, The Potential of Remote Sensing for Monitoring Rural Land Use Changes and Their Effects on Soil Conditions, *Agriculture Ecosystems & Environment*, **67(2-3)**: 197-209.

Staenz K, Brown RJ and Teillet PM, 1984, Infl uence of the viewing geometry on vegetation measures, Proceedings of the 8th Canadian Symposium on Remote Sensing, Montreal, QUE, (Canadian Remote Sensing Society), 5–12.

Steyaert LT, Hall FG and Loveland TR, 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 IL and McKallcock G, 1984, Determining the confidence level for a classification, *Photogrammetric Engineering and Remote Sensing*, **50**: 1491–1496.

Torrens PM and O'Sullivan D, 2001, Cellular automata and urban simulation: Where do we go from here? *Environment and Planning,* **28 (2)**: 163-168.

Townshend JRG, Justice CO, Skole D, Malingreau JP, Cihlar J, Teillet P, Sadowski F and Ruttenberg S, 1994, The 1 km resolution global data set: needs of the International Geosphere – Biosphere Programme, *International Journal of Remote Sensing*, **15**: 3417–3441.

Tucker CJ, 1979, Red and photographic infrared linear combinations for monitoring vegetation, *Remote Sensing of Environment* , **8**: 127-150.

Turner BL II, Mayer WB and Skole DL,1994, Global Land Use and Land Cover Change: Towards an integrated programme of study, *Ambio,* **23(1)***: 91-95.*

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

Veldkamp A and Fresco LO, 1996, CLUE: A conceptual model to study the conversion of land use and its effects, *Ecological Modelling,* **85 (2/3)**: 253-270.

Viovy N, Arino O and Belward AS, 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, Sohl T and Howard S M, 1998, Regional characterization of land cover using multiple sources of data, *Photogrammetric Engineering and Remote Sensing*, **64**: 45–57.

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

Wiegand CL, Richardson AJ, Escobar DE and Gerbermann AH, 1991, Vegetation indices in crop assessments, *Remote Sensensing of Environment,* **35**: 105-119.

Wigmosta MS, Vail LW and Lettenmaier DP, 1994, A distributed hydrology vegetation model for complex terrain, *Water Resources Research*, **30**: 1665–1679.

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

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