1999


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LAND-COVER CHANGE DETECTION FOR THE TROPICS
USING REMOTE SENSING AND
GEOGRAPHIC INFORMATION SYSTEMS

A Dissertation
Submitted to the Graduate Faculty of the
Louisiana State University and
Agricultural and Mechanical College
in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy

in

The Department of Geography and Anthropology

by

Jane M. Read
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December 1999

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Funding for this project was provided by the National Science Foundation (award number SBR-9627957), and Space Imaging EOSAT through their Space Imaging Eosat Award Program. Travel funds were provided by the Robert C. West Field Research Award of the Department of Geography and Anthropology at Louisiana State University. An eight-month GIS internship with the Organization for Tropical Studies at La Selva Biological Station enabled me to live and work in the study site for an extended period.

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ABSTRACT

Changing land-cover in the tropics is a central issue in global change research. This dissertation used Landsat-TM data to examine processes of land-use and land-cover changes for a lowland tropical site in Sarapiquí, Costa Rica. Performances of selected image-processing methods to detect and identify land-cover changes were evaluated.

A land-cover time-series from 1960 to 1996 for the site was generated using maps derived from aerial photographs and Landsat-TM classifications. Changes in land-cover from 1986 to 1996 were evaluated using standard landscape indices, and interpreted in terms of their historical context. Dominant changes in the site during this decade included the breakup of extensive cattle ranches for large-scale plantation enterprises and small-scale farming. Colonization processes, improvements in access, and changes in export markets were identified as the major driving forces of change.

Evaluation of change-detection methods revealed that postclassification comparison performed significantly better than image differencing algorithms. Image differencing using mid-infrared bands performed the best of the differencing algorithms tested. Selection of a suitable change-detection method can be aided through examination of the individual band statistics for the specific area and problem in question. The univariate band differencing technique has potential for identification of 'hot spots' of change using Landsat-TM data.

Spatial pattern-recognition techniques to characterize complexity of Landsat-TM data were evaluated. Fractal dimension calculated using the triangular prism surface area method, and Moran's I index of spatial autocorrelation, clearly distinguished different land-cover types. Shannon's diversity index and the contagion metric were not found to be useful in characterizing the images. The use of fractal dimension, in conjunction with standard non-spatial descriptive band statistics, are seen as having great potential in characterizing unclassified remotely sensed data based on differences in land-cover types. These statistics could be further developed for rapid environmental monitoring.
CHAPTER 1
INTRODUCTION

LAND-USE AND LAND-COVER CHANGE

In a world of continued expanding population, the changing global environment is recognized as a major concern for many earth and atmospheric scientists, politicians, development agencies, conservation organizations, and land management agencies. Although Earth has undergone continuous and sometimes drastic environmental change throughout its history, the impacts of changes as a result of human activities are significant because of their pervasive and continuous nature, and the accelerated rate at which they occur. The three main drivers of global change recognized by the International Geosphere-Biosphere Program (IGBP) are changes in land-use, atmospheric composition and structure, and climate (Walker and Steffen 1996). Of these three forces, land-use and land-cover change (LUCC) currently, and for the next several decades, represents possibly the most important (Vitousek 1992), and is the focus of this dissertation.

Land-cover refers to the physical and biotic materials present on the Earth’s surface; land-use describes the human uses to which the land surface is put. Land-use and land-cover are inextricably linked: land-cover today is determined primarily by the human activities that make use of the physical and biotic character of the land, and in turn the physical and biotic conditions affect and determine potential land-uses (Meyer and Turner 1992; Turner, Moss, and Skole 1993). Land-use and land-cover change (LUCC) is a term that recognizes the connections and feedback mechanisms between the physical (land-cover) and social (land-use) aspects of human-induced terrestrial environmental change (Turner, Moss, and Skole 1993). The global effects of LUCC derive from i) the cumulative effect of widespread local and regional changes, and ii) the alteration of local systems that feed into global systems (Meyer and Turner 1992; Turner and Meyer 1991; Vitousek 1992).

LUCC plays an important role as a driver of global environmental change through altering the functioning of terrestrial ecosystems. The proximate causes of LUCC include activities that convert, modify, or maintain land-cover, such as deforestation, selective logging,
or the application of fertilizers to maintain productivity (Turner, Moss, and Skole 1993). The resulting changes in biogeochemical and hydrological cycles, biodiversity, climate, and other systems, can ultimately lead to problems such as desertification, land degradation, and reduced agricultural production, in addition to altering organic carbon and greenhouse gas fluxes.

**LAND-USE AND LAND-COVER CHANGE IN THE TROPICS**

Increasing human population in the tropics continues to promote rapid changes in land-use and land-cover – by the year 2000 it is estimated that almost half the world's population will reside in the tropics. The rapidity at which land-use and land-cover changes occur in the tropics prevents gradual adjustment of natural and social systems to changing conditions, thereby intensifying the impact of the changes.

Deforestation remains the key element of LUCC in the tropics (Houghton 1994; McGuffie et al. 1995; Myers 1993; Palubinskas et al. 1995). Data compiled by the Food and Agriculture Organization of the United Nations (FAO) and interpreted by Whitmore (1997), demonstrate that between 1981 and 1990 there was an annual loss of natural tropical forests worldwide of 15.4 million hectares, at an annual rate of 0.81% of the 1980 forest extent (Table 1.1). Almost half of this deforestation occurred in the Americas (Whitmore 1997). An additional 5.6 million hectares of tropical forests were altered by logging activities during the same period (Whitmore 1997).

Tropical forests are cleared or modified primarily for logging, cattle ranching, shifted cultivation, and permanent agricultural activities (Dale et al. 1993; Malingreau and Tucker 1988; Myers 1993; Singh 1986). These proximate causes of deforestation and alteration of forests vary geographically, although shifted cultivation is widespread and has been identified as the primary proximate cause of tropical deforestation worldwide (Myers 1994). Rapid conversion of forests for cattle pastures has been associated primarily with Central American

---

1 Shifted cultivators are described as small scale farmers, who were landless or otherwise displaced from their original homes, and who migrated to tropical forest areas (Myers 1994).
<table>
<thead>
<tr>
<th>Area of forest in 1990 (millions ha)</th>
<th>Total forest loss 1981-1990 (millions ha)</th>
<th>Annual rate of loss (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Africa 527 (30%)</td>
<td>41</td>
<td>0.72%</td>
</tr>
<tr>
<td>Asia 311 (18%)</td>
<td>39</td>
<td>1.1%</td>
</tr>
<tr>
<td>America 918 (52%)</td>
<td>74</td>
<td>0.75%</td>
</tr>
<tr>
<td>Global Total 1,756</td>
<td>154</td>
<td>0.81%</td>
</tr>
</tbody>
</table>

Rates calculated as the percentage of forest existing in 1980.
Source: Whitmore 1997
and Amazonian frontier regions (Myers 1994), whereas logging activities have affected mostly the South American and Asian forests (2.45 and 2.15 million hectares annually from 1981 to 1990 respectively (Whitmore 1997). Often, logging activities promote the opening up of frontier regions and subsequent deforestation, as shifted cultivators follow the construction of logging roads.

Patterns of land-use shift through time as available forestland is exhausted and frontiers close (Figure 1.1). Continuing population increase puts pressure on land, often promoting changes in land-uses. Case studies of LUCC throughout the tropics demonstrate the many different trajectories of change that occur as physical and biotic, and socioeconomic conditions change (e.g. Collier, Mountjoy, and Nigh 1994; Dimyati et al. 1996; Hiraoka 1995; Kull 1998; Sader et al. 1997; Sierra and Stallings 1998; Skole et al. 1994; Virgo and Subba 1994).

**LUCC RESEARCH PRIORITIES**

The number and magnitude of multidisciplinary national and international research and monitoring programs focusing on global change, all of which to some extent focus on human-environment interactions, are testimony to the need for research on LUCC (Table 1.2). Indeed, LUCC research is the focus of the joint IGBP/IHDP LUCC core project, and comprises large components of the IGBP's Global Change and Terrestrial Ecosystem core project and Brazil's Large-scale Biosphere-Atmosphere Experiment in Amazonia (LBA) project.

In order to understand how LUCC affects and interacts with global earth systems, more information is needed on what changes occur, where and when they occur, and the social and physical forces that drive those changes (Lambin 1997). Despite ongoing research efforts on land-cover and land-use patterns since the 1980s, there remains a need for more basic land-cover and land-use data (Furley 1995), and for multidisciplinary studies (Skole et al. 1994) combining physical and biotic, and social information.

Although large-scale studies are useful for compiling change information rapidly over large areas, there is a need for local-scale studies because LUCC essentially operates at local scales, only becoming a global phenomenon through cumulative change (Meyer and Turner 1994).
Figure 1.1. Typical pathways of land-use changes in the tropics

(Adapted from Lambin 1997)
Table 1.2. Global change research and monitoring programs

<table>
<thead>
<tr>
<th>Program</th>
<th>Mother organizations</th>
<th>Duration</th>
<th>Focus areas</th>
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<tr>
<td>NON-GOVERNMENTAL INTERNATIONAL PROGRAMS</td>
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<td></td>
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<tr>
<td>DIVERSITAS Program of Biodiversity</td>
<td>ICSU, UNESCO</td>
<td>1991</td>
<td>Biological diversity – origins, composition, function, maintenance,</td>
</tr>
<tr>
<td>International Human Dimensions Program on Global Environmental Change (IHDP)</td>
<td>ISSC, ICSU</td>
<td>1990</td>
<td>Physical, chemical and biological processes regulating the total earth</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>system. Changes and human influences.</td>
</tr>
<tr>
<td>International Hydrological Program (IHP)</td>
<td>UNESCO</td>
<td>1975</td>
<td>Human-environment interactions and consequences.</td>
</tr>
<tr>
<td>World Climate Research Program (WCRP)</td>
<td>WMO, ICSU, UNESCO</td>
<td>1980</td>
<td>Individual/society responses to change. Impacts of policy responses on</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>economic and social conditions.</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Global hydrological cycle functioning. Human activities.</td>
</tr>
<tr>
<td>UNITED STATES GOVERNMENT PROGRAMS</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>U.S. Global Change Research Program</td>
<td>U.S.</td>
<td>1990</td>
<td>Coordinates with international programs and national initiatives</td>
</tr>
<tr>
<td>Earth Science Enterprise (ESE)</td>
<td>NASA</td>
<td>1998-2002</td>
<td>Total Earth system; effects of human on the global environment</td>
</tr>
<tr>
<td>National Science Foundation Global Change Research Programs</td>
<td>NSF</td>
<td></td>
<td>Physical, biological, and socioeconomic systems, includes the</td>
</tr>
<tr>
<td>Climate and Global Change Program</td>
<td>NOAA</td>
<td>1989</td>
<td>Human Dimensions of Global Change (HDGC) program</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Climate variability.</td>
</tr>
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Sources: web pages of different programs.
Local and regional scale studies take into consideration local and regional differences, which allow the identification of sets of driving forces of LUCC for different environments. These could then be applied to global models, thus enabling more sophisticated modeling scenarios more in line with the complexity of the problem (Lambin 1997). Moreover, local conditions have been shown to combine with large-scale external forces to influence regional trends (Skole et al. 1994).

Land-use is not only influenced by extant environmental and social conditions. Historical land-cover conditions shape subsequent land-uses through altering both the human, and the physical and biotic environments; thus, compilation of historical environmental and social case study data for integration with more recent data is a priority (Lambin 1997; Xavier and Szewach 1998).

REMOTE SENSING AND GIS IN LUCC RESEARCH

Land-use studies in the tropics require access to land-cover data for sites which often encompass large areas, and which can be relatively inaccessible and poorly mapped. The data must be collected simultaneously over the study area, with suitable temporal and spatial resolutions. The data must be unbiased, rapidly interpretable, and permanent. Satellite remote sensing data are meeting these requirements (Xavier and Szewach 1998).

In recent years the identification of needs for detailed environmental information by international initiatives (Table 1.2) has fuelled advancements in geographic information science, resulting in improvements in remote sensor technologies, increased diversity of sensors and data characteristics, and improvements in software and data handling. The number and variety of sensors gathering information about the surface of the earth have increased dramatically since the first Landsat (then Earth Resources Technology Satellite) satellite went into orbit in 1972 (Lillesand and Kiefer 1994). In April 1999 Landsat 7 was successfully launched.

Terabytes of data are downloaded and archived each day from the dozens of governmental and commercial sensors orbiting the earth. Recent developments in the availability of hyperspectral data, and data collected at fine (5m and 1m) spatial resolutions,
promise to be invaluable for land-cover change studies. Such data will allow for more detailed land-cover mapping, which to date has been restricted by the spatial resolution of affordable data, such as Landsat Thematic Mapper data. The increased availability of different remote sensing sources will also permit multi-scale studies, which are needed for scaling up and down of results for land-use change modeling (Xavier and Szejwach 1998). In line with improvements in sensor technologies, necessary improvements in computing and geographic information systems have permitted the integration of historic and current spatial data, gathered from many different sources including aerial photographs and satellite remote sensors, with social land-use data.

With the generation of so much digital land-cover information, there is a real need for further research in the digital image-processing arena. Without the added complications that vast quantities of hyperspectral data will bring, there remain fundamental research questions concerning the extraction of land-cover and land-use information from remote sensing data. These include the selection of the most appropriate methods to detect changes, especially when integrating data from different sensors. A better understanding of the performance of standard change detection methods is necessary if the results are to be incorporated with other data in global land-use models.

**SCOPE OF THE DISSERTATION**

The goals of this dissertation research were twofold. The first goal was to understand the spatial and temporal processes of human-induced land-use/cover changes in a lowland tropical environment, and to identify the forces driving such changes. The second goal was to identify suitable methods using remote sensing and geographic information systems to detect and identify land-cover change in the tropics.

The specific objectives were to i) identify and map historical and current changes in land-cover and land-use in a lowland tropical site from 1960 to 1996, ii) identify the causal processes and driving forces of those land-use changes, iii) identify suitable methods to detect land-cover changes, through evaluating the performance of selected remote sensing image processing and GIS techniques using multitemporal Landsat Thematic Mapper (TM) data for
the same site, and iv) identify suitable methods to extract spatial characteristics of land-cover, through evaluating fractal dimension, spatial autocorrelation, and standard landscape indices, using unclassified Landsat-TM data.

RESEARCH SITE

The study area was located in the Caribbean lowlands of northeastern Costa Rica in Sarapiquí Canton, Province of Heredia (Figure 1.2). It encompassed approximately 35km by 40km of lowland forests and agricultural lands.

The site was selected for a number of reasons. First, most human-induced changes occurred during the last 50 years, and have been well documented. Aerial photographs date back to the 1950s, and population and agricultural data for the period are available from census sources. In addition, the good oral record that exists facilitates a reconstruction of the history of the area. These combined data sources permit in-depth studies of the nature of land-cover and land-use changes. Second, existing studies of the history of colonization and agricultural development of the region provide good sources of socioeconomic information (e.g. Butterfield 1994a; Pierce 1992b; Schelhas 1991). Lastly, the area encompasses an array of different land-uses, including protected and unprotected areas, and has undergone rapid change since the frontier was first opened.

This study can be useful in a regional context because the proximate causes of change experienced in the site are typical of many lowland tropical areas, and include subsistence farming, permanent and plantation agriculture, cattle ranching, and infrastructure development. Sarapiquí represents a region that has gone from being an open frontier to one that contributes significantly to the nation’s agricultural export economy.

ORGANIZATION OF THE DISSERTATION

The dissertation comprises six chapters, including this introduction to the topic of land-use and land-cover change. LUCC represents the main theme of the dissertation — one of the topics at the forefront of global change research today. This study explores methods using geographic information systems and remote sensing technologies to enhance our understanding of LUCC in a lowland tropical environment. The document is organized in
Figure 1.2. Location of study site, Sarapiquí, Costa Rica
journal style, with separate introductory and methods sections included in each of the three main chapters (Chapters 3, 4, and 5).

Chapter 2, Methods, describes the general methods used in the generation of the land-cover time-series, which represented the primary data source for the research described in Chapter 3, and reference data for research presented in Chapters 4 and 5. Chapter 3, the first of the main research chapters, Land-Cover and Land-Use Changes in the Sarapiquí Region of Costa Rica: 1960 to 1996, investigates the changes in land-cover that occurred in the study site from 1960 to 1996, and attempts to explain those changes in terms of their driving forces. Chapter 4, Comparison of Digital Spectral Pattern Recognition Change-Detection Methods, then describes the results of research evaluating the performances of selected standard image-processing techniques to detect changes using the spectral characteristics of Landsat-TM data. And, Chapter 5, Comparison of Digital Spatial Pattern Recognition Indices for Characterizing Land-Cover from Remote Sensing Data, presents results of research investigating the use of spatial pattern-recognition methods to characterize differences in land-cover types. Finally, Chapter 6, Conclusions, ties the findings of Chapters 3, 4, and 5 together, and presents suggestions for future research directions.

REFERENCES


CHAPTER 2
METHODS

INTRODUCTION

This dissertation research was based on a case study of LUCC for a lowland tropical environment in Costa Rica. It employed geographic information systems with remote sensing data to generate a time-series of land-cover information for the study area for the period 1960-1996. This land-cover time-series was used, in combination with literature research and field observations, to examine the relationships between land-cover, land-use, and the driving forces of change for both present-day and historical contexts. In addition, the LUCC information was used to test the performance and accuracy of selected standard image processing change detection methods, and the sensitivity of landscape indices in context of land-cover and land-cover changes in the study area, using Landsat Thematic Mapper data from 1986 and 1996.

Field research was conducted in two phases: phase I from January to August 1996, and phase II June-August 1997. Field work comprised two aspects: i) compilation of land-cover/land-use data for generating the dataset, and ii) collection of secondary source data and literature on the history of the region. The global positioning system (GPS) was used to collect ground control points (GCPs) during the summer of 1997 for georeferencing the dataset, as well as collection of spatially-referenced ground information for classifying and assessing the accuracy of the 1996 land-cover map.

Primary software used in analyses and development of the dataset were ArcINFO and ArcView (ESRI, Redlands, CA), and ERDAS Imagine (ERDAS, Inc., Atlanta, GA).

DEVELOPMENT OF THE LAND-COVER TIME-SERIES

Primary data sources

The land-cover time-series, comprising land-cover maps for 1960, 1983, 1986, 1992, and 1996, was derived from black-and-white aerial photographs and Landsat Thematic Mapper (Landsat-TM) images (Figure 2.1). The availability of aerial photograph sets and
Figure 2.1. Generation of the land-cover time-series
cloud-free Landsat-TM images of the site determined the dates for the individual land-cover
data layers.

Landsat data for Central America are available to customers in the United States from
the archives of the U.S. Geological Survey, EROS Data Center in Sioux Falls, SD, or Space
Imaging EOSAT Co., Lanham, MD. Few cloud-free satellite images for the area exist (World
Reference System path/row 15/53), as is often the case in lowland tropical environments. A
high quality cloud-free image was obtained for 1986, however more recent images had
extensive cloud-cover and haze obscuring the study area. Consequently, a composite
classification of two images (1996 and 1997) was used to derive the 1996 land-cover map
(see later), and a cloud-covered image from 1993 was obtained and used for reference only
(Table 2.1).

Aerial photograph sets for development of land-cover maps were selected based on
the most complete coverage of the site (Figure 2.2), dates that spanned a representative
period of the history of significant change in the site, and similarity of scale between the aerial
photograph sets (Table 2.1).

Ground reference data

GPS positions were collected from July to August 1997 using a Trimble Pathfinder
Community Base Station and rover unit. The majority of positions were differentially corrected
(post-processing) to give positional accuracies of ± submeter to 5 meters\(^1\) (Table 2.2). The
base station antenna was set up over a point located on the roof of the dining room of La
Selva Biological Station, with an unobstructed view of the sky in all directions. The base
station antenna position was determined by averaging more than 412,000 positions collected
between July 2 to August 12 1997.

A total of 495 point positions, with accompanying land-cover descriptions, were
recorded (Figure 2.3). A local guide, Rodolfo Vargas Ramírez, accompanied each excursion
and was consulted for land-cover and land-use information at each location. Positions were

\(^1\) Positions recorded under dense canopy cover, which are subject to multipath error, are likely
to have lower accuracy than the sub- to 5 meters stated.
Table 2.1. Data sources

<table>
<thead>
<tr>
<th>Data type</th>
<th>Mission</th>
<th>Date Acquired</th>
<th>Data Reference</th>
<th>Obtained from</th>
</tr>
</thead>
<tbody>
<tr>
<td>Landsat-TM</td>
<td>Landsat 5</td>
<td>21 December 1997</td>
<td>5015053009735510</td>
<td>EROS Data Center (EDC), Sioux Falls, SD</td>
</tr>
<tr>
<td>Landsat-TM</td>
<td>Landsat 5</td>
<td>16 November 1996</td>
<td>5015053009632110</td>
<td>Space Imaging EOSAT Co., Lanham, MD</td>
</tr>
<tr>
<td>Landsat-TM</td>
<td>Landsat 4</td>
<td>8 May 1993</td>
<td>4015053009312810</td>
<td>EDC, Sioux Falls, SD</td>
</tr>
<tr>
<td>Landsat-TM</td>
<td>Landsat 5</td>
<td>6 February 1986</td>
<td>5015053008603710</td>
<td>EDC, Sioux Falls, SD</td>
</tr>
<tr>
<td>Panchromatic aerial</td>
<td>?</td>
<td>18 January 1992</td>
<td>Roll-4 ST-27B #873-881</td>
<td>Instituto Geográfico Nacional (IGN), San Jose, Costa Rica</td>
</tr>
<tr>
<td>photographs (1:60,000)</td>
<td>MAG</td>
<td>January 1983</td>
<td>Roll-1 ST-36 v#215-219</td>
<td>IGN, San Jose, Costa Rica</td>
</tr>
<tr>
<td>Panchromatic aerial</td>
<td>MAG</td>
<td>January 1983</td>
<td>Río Cuarto/Río Suced, ph # 72-85; 95-103; 112-126</td>
<td>IGN, San Jose, Costa Rica</td>
</tr>
<tr>
<td>photographs (1:60,000)</td>
<td>USAF 1370PMW</td>
<td>11 March 1960</td>
<td>Roll 28, ph # 3043-3048</td>
<td>IGN, San Jose, Costa Rica</td>
</tr>
<tr>
<td>Panchromatic aerial</td>
<td>USAF 1370PMW</td>
<td>12 March 1960</td>
<td>Roll 29, ph # 3169-3176</td>
<td>IGN, San Jose, Costa Rica</td>
</tr>
<tr>
<td>GPS equipment</td>
<td>Base station</td>
<td>Trimble Pathfinder Community Base Station: 12 channel Antenna: compact L1 w/ groundplane.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>---------------</td>
<td>--------------</td>
<td>------------------------------------------------------------------------------------------</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Rover unit</td>
<td>Trimble Pathfinder Pro XL System: 6 channel receiver, TDC1 Data Collector</td>
<td></td>
<td></td>
</tr>
<tr>
<td>General data collection</td>
<td>Autonomous horizontal accuracy</td>
<td>Up to 100m (95% 100m; 68% 50m; 50% 40m)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Differentially corrected horizontal accuracy</td>
<td>Submeter to 5m (95% 2 m; 68% 1m; 50% 0.8m)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Coordinate system</td>
<td>UTM meters zone 16</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Datum</td>
<td>WGS-84</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Position collection</td>
<td>PDOP</td>
<td>≤ 6.0</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SNR</td>
<td>≥ 6.0</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Elevation mask</td>
<td>15</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Number of satellites</td>
<td>≥ 4</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Figure 2.3. Routes and positions recorded using the global positioning system.
primarily taken along roads and trails where land-cover either side of the road or trail i) represented a land-cover type not previously recorded, ii) represented a land-cover type clearly identifiable on a hardcopy of either the 1986 or 1996 images, iii) changed abruptly, or iv) represented change between 1986 and 1996 as identified from the images.

Georeferenced photographs representative of all land-cover categories were taken. Field notes with compass directions describing land-cover/land-use conditions were recorded at each GPS position. In addition to gathering land-cover/land-use data, road routes and major road intersections and bridges were recorded.

Classification Scheme

A common classification scheme, following the hierarchical principles of the USGS land-cover classification system (Anderson et al. 1976), was adopted for all final land-cover classifications (Table 2.3). The classifications were developed with forest and agricultural land-uses as the categories of primary interest.

Landsat-TM Image Processing

i) Georeferencing and rectification

Subsets of the study area, approximately 1400 by 1200 pixels (1360km²), were created from the original Landsat-TM images. The 1996 Landsat-TM subset was georeferenced to Universal Transverse Mercator (UTM) meters based on the GPS-derived ground coordinates (UTM zone 16; datum WGS-84). The 1997, 1993 and 1986 subsets were subsequently transformed to the 1996 georeferenced file. A pixel-pixel rectification accuracy of 0.5 pixel was required. All coordinate transformations used nearest neighbor, first order polynomial transformations, with a 28.5m cell size (Table 2.4).

Independent assessments of accuracy of georeferencing, and rectification of the data layers to the 1996 georeferenced subset, were conducted using GCPs independent of those used in the actual transformations (Table 2.4). It should be noted that the quality of the GCPs used in the independent checks was not as high as that for the rectification procedure because the best potential GCP points had already been used for the rectification itself. Consequently, accuracy is likely to be greater than those suggested by the independent
Table 2.3. Classification scheme

<table>
<thead>
<tr>
<th>Level-1</th>
<th>Level-2</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urban</td>
<td>Urban</td>
<td>Buildings (residential, agricultural, commercial); roads</td>
</tr>
<tr>
<td>Agriculture</td>
<td>Pasture</td>
<td>Pastures used primarily for cattle. May include pastures with some degree of tree cover, although not closed canopy.</td>
</tr>
<tr>
<td>Forest</td>
<td>Forest</td>
<td>Closed canopy forest. May include undisturbed old growth, selectively-logged, secondary.</td>
</tr>
<tr>
<td>Scrub</td>
<td>Scrub</td>
<td>Intermediate category of scrubby vegetation. Includes a gradient from disturbed/regenerating forest with closed cover to pasture with almost closed tree cover.</td>
</tr>
<tr>
<td>Barren</td>
<td>Barren</td>
<td>Unsuitable for agriculture (= river beaches).</td>
</tr>
<tr>
<td>No data</td>
<td>No data</td>
<td>No data (mixed classes of clouds, cloud shadows, lakes, rivers)</td>
</tr>
</tbody>
</table>
Table 2.4. Georeferencing and rectification transformations

<table>
<thead>
<tr>
<th>Data layer</th>
<th>Registered to</th>
<th>Transformation RMSE (pixel)</th>
<th># control points</th>
<th>Independent check RMSE (pixel)</th>
<th># control points</th>
</tr>
</thead>
<tbody>
<tr>
<td>Landsat-TM 1997</td>
<td>1996 georeferenced file</td>
<td>0.268</td>
<td>18</td>
<td>0.345</td>
<td>10</td>
</tr>
<tr>
<td>Landsat-TM 1996</td>
<td>GPS UTM meters</td>
<td>0.198</td>
<td>13</td>
<td>0.474</td>
<td>11</td>
</tr>
<tr>
<td>Landsat-TM 1993</td>
<td>1996 georeferenced file</td>
<td>0.250</td>
<td>7</td>
<td>0.364</td>
<td>11</td>
</tr>
<tr>
<td>Landsat-TM 1988</td>
<td>1996 georeferenced file</td>
<td>0.297</td>
<td>8</td>
<td>0.431</td>
<td>11</td>
</tr>
</tbody>
</table>
These assessments showed rectification accuracies of better than 0.5 pixel for all data layers.

ii) Image normalization

In order to reduce the differential effects of haze and other external factors, the 1986 and 1996 image subsets were normalized using a linear regression technique. The procedure involved identifying features that were consistent for both images. In this study the most consistent features identifiable between the two images were old growth forest, deep lakes, rivers, and banana plantations. The lack of strong seasonality operating in the site, and the relatively short, two-and-a-half-month period, between acquisition of the images (November to February) were seen as factors which would minimize the differences in reflectances typical of these features. Contiguous samples of nine pixels for each of seven features were used to calculate regression coefficients for each band. Individual samples were assessed based on their residual values. R-square values were greater than 0.9 for all bands, except the thermal band. The calculated regression equations were then applied to the 1996 image. An examination of the results of this procedure demonstrated that this method was successful in reducing the differences between brightness values of the two scenes.

iii) Removal of clouds and cloud shadows

Pixels affected by clouds and their shadows for the 1996 and 1997 images were identified using the tasseled cap transform (components 1 and 4), and/or unsupervised classification, and masked out of the scene. The 1986 image had very few clouds over the study site, and cloud-affected pixels were masked out manually.

iv) Unsupervised land-cover classifications

The 1986, 1996 and 1997 cloud-free Landsat-TM subsets were classified using an unsupervised classification (ISODATA routine in IMAGINE (ERDAS 1995)) generating 100 initial classes from all seven TM bands. The class signatures were assessed using class separability statistics and feature space images, and classified through visual examination of classes on color composite displays of the image, in conjunction with reference data (GPS field data, aerial photograph interpretations, and color composite displays of the 1993

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Landsat-TM image). The classes were recoded to the classification system described in Table 2.3. Pixels in mixed/unidentified classes were separated out and the ISODATA routine rerun on those pixels. The classes were interpreted and classified as before and the classified pixels merged back with the remainder of the image. A 3x3 window majority filter was passed over the image to eliminate speckling.

To minimize the areas of 'no data' on the 1996 classification as a result of clouds and their shadows, the 1997 classified image was overlaid on the 1996 classification and pixels that represented 'no data' were replaced with the 1997 class values where possible. The resulting classification is hereafter known as the 1996 classification.

The 1986 and 1996 land-cover classifications were vectorized, and all polygons less than 3 hectares (≤37 pixels) were eliminated. Subsets comprising the common area covered by all data layers of the classifications were checked for logical consistency against the other land-cover maps in the time-series, and labels and polygon arcs edited where necessary using the aerial photograph data as 'truth' (see below).

Aerial Photograph Processing

Black-and-white aerial photographs (1:60,000 scale) were visually interpreted using a zoom transfer scope by J. Denslow and S. Guzman, Dept of Biological Sciences, Louisiana State University. Land-cover patches, roads, and rivers were traced at a scale of approximately 1:25,000 onto mylar using enlarged Costa Rican 1:50,000 topographic maps for control (Río Cuarto Hoja 3347 II; Río Sucio Hoja 3447 III; Costa Rica Lambert Projection). The maps were subsequently digitized and converted to UTM meters. Distortions in the aerial photographs, and systematic error in the Costa Rican base maps resulted in discrepancies between the UTM coordinates of the satellite image files and the aerial photograph files. To minimize these errors the aerial photograph UTM layers were subsequently rectified, using either nearest neighbor first order polynomial transformations or rubber-sheeting (depending on the severity of the distortions), to the 1986 Landsat-TM subset, that year being the closest to the dates of the aerial photographs, thus allowing selection of better quality control points.
It was not possible to conduct independent tests of the accuracy of rectification of these maps owing to the lack of identifiable control points: all available points had been used in the rectification process. The land-cover patches were coded to conform to the classification scheme described above. Polygons less than three hectares were eliminated.

Assessment of the land-cover time-series

i) Classification scheme

The classification scheme was developed, not only based on categories of interest, but also on the data characteristics of both the Landsat-TM and aerial photograph data. Inherent differences between the Landsat-TM and aerial photograph data, and thus the methods and ability to extract land-cover information from them, effectively restricted the resolution of the common classification scheme. Whereas the Landsat-TM data were interpreted using spectral characteristics, the aerial photographs were interpreted using a combination of spectral and visual pattern recognition techniques. These differences, in addition to differences in spatial and spectral resolutions, resulted in differential performances of the two data types in identifying different land-cover categories. The resulting scheme comprised four primary classes of interest, which could be identified from all data layers: forest, pasture, crops, and scrub.

Other land-use categories identified on the aerial photographs and Landsat-TM classifications included river beaches ('barren'), and areas covered by buildings ('urban'). Neither of these categories were consistently identified, nor represented significant proportions of the landscape.

ii) Spatial resolution of the land-cover maps

Land-use patterns manifest at scales smaller than the minimum mapping unit of three hectares, were not identifiable on the land-cover maps. These included isolated buildings, and houses with gardens, and small farms of mixed agriculture. Because most buildings and houses are associated with pastures, the majority of these areas were classified as pasture. Likewise, small farms under mixed agriculture but comprising a relatively large proportion of pasture, were classified as pasture rather than crops, thereby resulting in overestimation of
the proportion of pasture in the landscape and underestimation of the area in cropland.

Another land-use that was effectively excluded from the land-cover maps was reforestation programs, which comprise small areas, mostly less than three hectares, of forestry plantations (P. Rojas, pers. comm.).

iii) Thematic accuracy

There was no way to determine the thematic accuracy of the historic land-cover maps derived from the aerial photographs, these being the most detailed source of land-cover information available. Where possible the aerial photograph interpretations were visually checked using the available satellite imagery and field and literature information. The overall quality of the land-cover classifications from the aerial photographs appeared good.

Assessments of the Landsat-TM classifications were possible using the aerial photograph interpretations as reference data. This assumed that the aerial photograph interpretations were ‘correct’. In order to assess the classifications using all possible reference sources, the assessments included only the common area covered by all data layers. The 1986 Landsat-TM classification was assessed using the 1983 land-cover map as reference data, in conjunction with the 1992 map to allow for changes that occurred between 1983 and 1986. The 1996 classification was assessed primarily using a subset of GPS-derived field reference data, but also in conjunction with the historic land-cover information provided by the aerial photograph interpretations.

Thematic accuracies were assessed using standard contingency tables (Tables 2.5 and 2.6)\(^1\). Sample sizes of approximately 50 per class were selected using stratified random sampling. The sample unit represented a single pixel at the center of a 3x3 window of pixels classified as the same category.

The overall accuracy for the 1986 and 1996 classifications were 85% and 89% respectively. The overall measures of accuracy provided by the kappa statistic were 79% and 83% respectively, with narrow confidence intervals (Tables 2.5 and 2.6). The slightly poorer

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\(^1\) A detailed explanation of the statistics used for accuracy assessment is given in Chapter 4.
Table 2.5. Contingency table of classification accuracy: 1986 Landsat-TM land-cover classification

<table>
<thead>
<tr>
<th>CLASSIFICATION</th>
<th>F</th>
<th>P</th>
<th>C</th>
<th>Sc</th>
<th>Row Total</th>
<th>Producer's Accuracy</th>
<th>User's Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>F</td>
<td>61</td>
<td>2</td>
<td>0</td>
<td>6</td>
<td>69</td>
<td>0.924</td>
<td>0.884</td>
</tr>
<tr>
<td>P</td>
<td>0</td>
<td>51</td>
<td>10</td>
<td>3</td>
<td>64</td>
<td>0.911</td>
<td>0.797</td>
</tr>
<tr>
<td>C</td>
<td>0</td>
<td>0</td>
<td>33</td>
<td>0</td>
<td>33</td>
<td>0.787</td>
<td>1</td>
</tr>
<tr>
<td>Sc</td>
<td>5</td>
<td>3</td>
<td>0</td>
<td>21</td>
<td>29</td>
<td>0.7</td>
<td>0.724</td>
</tr>
<tr>
<td>Column Total</td>
<td>66</td>
<td>56</td>
<td>43</td>
<td>30</td>
<td>185</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

F = forest; P = Pasture; C = Crops; Sc = Scrub

Producer's accuracy = diagonals/col total
User's accuracy = diagonals/row total
Overall accuracy (sum diagonals/total) = 166/185 = 0.851

Kappa Coefficient of Agreement = 0.79
Variance of kappa = 0.001
z-statistic = 22.95
95% confidence interval for kappa: 0.7902 < kappa < 0.7999
Table 2.6. Contingency table of classification accuracy: 1996 Landsat-TM land-cover classification

<table>
<thead>
<tr>
<th>REFERENCE</th>
<th>F</th>
<th>P</th>
<th>C</th>
<th>Row Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>F</td>
<td>62</td>
<td>4</td>
<td>0</td>
<td>66</td>
</tr>
<tr>
<td>P</td>
<td>2</td>
<td>54</td>
<td>9</td>
<td>65</td>
</tr>
<tr>
<td>C</td>
<td>1</td>
<td>6</td>
<td>60</td>
<td>67</td>
</tr>
<tr>
<td>Column Total</td>
<td>65</td>
<td>64</td>
<td>69</td>
<td>198</td>
</tr>
</tbody>
</table>

Producer's Accuracy = diagonals/col total
User's accuracy = diagonals/row total
Overall accuracy (sum diagonals/total) = 176/198 = 0.889

Kappa Coefficient of Agreement = 0.83
Variance of kappa = 0.001
z-statistic = 24.90
95% confidence interval for kappa: 0.6286 < kappa < 0.8380

F = forest; P = Pasture; C = Crops;
NB: scrub category was not evaluated because it represented a negligible proportion of the landscape.
performance of the 1986 classification in relation to the 1996 classification was in part a
to the inclusion of the scrub category in the 1986 assessment; scrub was excluded
from the 1996 assessment on the grounds that the class represented a negligible proportion of
the area that would not have provided a sufficiently large sample size for testing. The z-
scores demonstrated both error matrices to be significantly different from random results, and
the test for differences between the 1986 and 1996 matrices revealed them to be not
significantly different from each other, suggesting that the two classifications were
comparable.

An examination of the contingency matrices demonstrated that forest was generally
well classified, with relatively good User's and Producer's accuracies for both classifications.
On both the 1986 and 1996 classifications there was confusion between agricultural crops and
pasture, with crops classified as pasture. These areas may represent low-growing crops with
bare ground showing between rows, which would produce a similar signature to some
pastures. The pineapple and banana plantations, however, were consistently correctly
classified as crops, presumably as a result of their distinctive signatures. The scrub class was
not reliably identified on the satellite images, and is under-represented on the Landsat-TM
classifications. This is because scrub represents an intermediate stage between forest and
non-forest vegetation, from being either a very dense cover of secondary vegetation, to
pasture with a high proportion of tree cover. It was estimated that approximately equal
proportions of scrub were classified as pasture and forest, thereby inflating the proportion of
land classed as those categories.

Summary

The land-cover time-series comprises medium-scale land-cover maps with a minimum
mapping unit of 3 hectares, suitable for analysis of forest, pasture, and agricultural crops for
methods used to derive the maps, direct comparisons are valid only between the 1960, 1983
and 1992 layers (derived from aerial photographs), and between the 1986 and 1996 (derived
from Landsat-TM data) layers. Trends in the data, and trajectories of change, across all
layers however, are valid. The integration of the two data types highlighted some of the
problems associated with combining data of different characteristics, but also provided a
useful landscape- and regional-scale tool for assessment of land-cover through time that
would otherwise not have been possible.

REFERENCES

and land cover classification system for use with remote sensor data. Geological

CHAPTER 3
LAND-COVER AND LAND-USE CHANGES
IN THE SARAPIQUÍ REGION OF COSTA RICA: 1960 TO 1996

INTRODUCTION

In the context of Costa Rica’s continuing population increase, its agriculturally based export economy, its strong protected area network, and the increasing economic importance of tourism, this study will examine the spatial and temporal dynamics of land-use and land-cover changes (LUCC) for a lowland tropical environment in Costa Rica. The Sarapiquí region went from being a relatively isolated and sparsely populated frontier in 1950, to one of the country’s most active colonization zones (Butterfield 1994a), a major producer of export crops, and a destination for ecotourists attracted to the Braulio Carrillo National Park and private reserves.

A rich literature documents the increase in population, the history of colonization, and changing land-use practices in Costa Rica. This has been made possible through efforts of the Costa Rican government agency, the Dirección General de Estadística y Censos, which has been responsible for the long history of population censuses dating back to the 1880s, and agricultural censuses, which date back to 1950¹. Few studies of sites in the humid tropics have access to such a comprehensive set of socioeconomic information. There is also an impressive archive of reliable land-cover information, dating back to the 1950s for much of the country, including parts of Sarapiquí, in the form of black and white aerial photographs, which were commissioned largely by the government. This combination of historical socioeconomic and land-cover information is invaluable when attempting to place current processes of land-use and land-cover changes in historical context.

The issue of land-cover and land-use change in Costa Rica, and specifically deforestation, has been the focus of studies since the 1980s, fuelled by concern for the extremely high deforestation rates in Central America, and Costa Rica in particular (Centro

¹ The absence of a census in the early 1990s however, has created a serious void in the data series.
Cientifico Tropical 1982; Houghton, Lefkowitz, and Skole 1991; Myers 1988; Nygren 1995; Whitmore 1997). These studies have been facilitated by the availability of historic census and remote sensing data. At the country level, studies that have focused on rates and patterns of deforestation include those by Keogh (1984), Sader and Joyce (1988) and Sanchez-Azofeifa (1996). Others have examined the socioeconomic forces driving deforestation (e.g. Jones 1992; Lehmann 1992; Sanchez-Azofeifa 1996). However, few have attempted to integrate spatial land-cover and socioeconomic aspects for Costa Rica as a whole (but see Harrison 1991).

The physical patterns of land-use and land-cover changes resulting from effects of national-scale socioeconomic forces manifest themselves at local scales. The 1997 LUCC Data Requirements Workshop (Xavier and Szejwacht 1998) recognized the development of regional and local datasets as a priority. The need for regional studies relating deforestation and other land-cover changes to specific land-uses has also been recognized (Lehmann 1992). Regional accounts of the history of colonization and agricultural development in Sarapiquí include those by Pierce (1992a; 1992b), Butterfield (1994a), and Montagnini (1994). However, aside from studies of deforestation and forest fragmentation by Sanchez-Azofeifa (1995; 1999), a detailed study of the spatial aspects of land-cover changes for the area has not been carried out to date.

The research presented here will take advantage of the sources of historical socioeconomic information, and combine this with detailed historic and present-day land-cover and land-use data, in an attempt to explain the pattern of LUCC for a site in a region that continues to undergo profound change. The results of this study will provide specific spatial data on patterns of land-cover change, and will help to fill the gap generated by the lack of an agricultural census after 1983.

This paper addresses the first goal of this dissertation. The stated objectives were i) to identify and map historical and current changes in land-cover and land-use in a humid tropical site from 1960 to 1996, and ii) to identify the causal processes and driving forces of land-use change. The emphasis was on explaining changes that occurred from 1986 to 1996,
using Landsat Thematic Mapper remote sensing data. This was done through interpretation and analyses of land-cover maps derived from aerial photographs and Landsat-TM data, in conjunction with historic road networks derived from aerial photographs, and historic information from the literature, for the site in the Sarapiquí region of northeastern Costa Rica, Province of Heredia (Figure 1.2).

THE REGIONAL HISTORICAL SETTING: COSTA RICA TO THE MID-1990'S

Costa Rica's population grew from approximately 65,000 at independence (year 1821), with the majority confined primarily to the Central Valley or Pacific Plain, to over 2.2 million, residing virtually throughout the extent of the Republic, by 1980 (Augelli 1987; Hall 1985; Harrison 1991; Pierce 1992b). From 1850 to 1930 there was a dramatic increase in population, with the net rate of increase peaking in the 1850s (Harrison 1991). This increase in population promoted the start of internal migration out from the Central Valley and Pacific Plain, as the availability of farmlands was exhausted and opportunities for work appeared elsewhere (Hall 1985; Harrison 1991). Agricultural colonization, developments of the transport network, and establishment of centers of population ensued (Hall 1985; Lehmann 1992). Subsequent rapid population growth lead to accelerated agricultural colonization and exhaustion of the settlement frontiers circa 1965 (Augelli 1987; Hall 1985). Since then migration has been directed back to the cities, and land redistribution has taken the place of frontier colonization (Hall 1985; Harrison 1991).

Hall (1985) characterized the movement of people to the frontiers of settlement in terms of three forces: spontaneous colonization, plantation enclaves, and planned colonies. Spontaneous colonization probably had the most far-reaching effects on the movements and resulting distribution of the population. Spontaneous colonization started around 1850 and took the form of either gradual movement outward from the Central Valley as roads and railways opened up new areas, or pioneer colonization where colonists moved into more inaccessible regions, preceding the development of centers of population and infrastructure development (Hall 1985). In 1961 the Ley de Tierras y Colonización prohibited further spontaneous colonization.
The second force, plantation enclaves, developed as a result of investment in the banana industry by North American fruit companies, initially locating close to the coasts, and expanding into other areas only as transportation improved. The enclaves served to clear large areas of forestland, build roads and railways, provide jobs for the landless, and establish towns (Hall 1985).

The third mechanism, planned colonies, had little lasting impact compared with spontaneous colonization and the plantation enclaves. Prior to 1962 few colonies were successful. However, in 1962 the government created the Instituto de Tierras y Colonización (ITCO, now the Instituto de Desarrollo Agrario [IDA]), which was made solely responsible for agrarian reform. Between 1962 and 1966 ITCO established colonies on forest lands, after which it concentrated its efforts on land redistribution and the settlement of squatter disputes, rather than establishment of new colonies (Hall 1985). This took the form of ‘zonas de colonización’ which were derived from the purchase of state lands, and generally comprised large areas of 40 to 50 hectares which were distributed by ITCO (R. Schmidth, pers. comm.). Today IDA distributes ‘asentamientos’ of approximately five to six hectares, which derive from the purchase of underutilized privately owned lands. IDA either assigns ‘parcelas’ — small areas for agricultural purposes, or ‘lotes’ — smaller areas for houses with gardens (R. Schmidth, pers. comm.).

The major impact on land-cover of the movement of population out from the center of the country was deforestation. An estimated 99.8% of Costa Rica was originally forested (Centro Científico Tropical 1982). Estimates of forest cover for Costa Rica vary depending on the methods of calculation, and the definitions and types of forest being represented; however, there is consensus that from 1940 to present there has been a dramatic decrease in area of forest (Augelli 1987; Centro Científico Tropical 1982; Harrison 1991; Keogh 1984; Sader and Joyce 1988). Approximately 20,000 square kilometers of forest, or almost 60,000 hectares per year on average, were cleared between 1950 and 1984 (Harrison 1991; Sader and Joyce 1988). Sader and Joyce (1988), using maps based on aerial photographs and Landsat-MSS
data, demonstrated that both the absolute rate and the relative rate of deforestation were highest from 1977 to 1983. The only countywide data available on forest cover for Costa Rica after 1983 is that produced by Sanchez-Azofeifa (1996). Sanchez-Azofeifa's data (1996) for the central part of Costa Rica, derived from Landsat-TM images, suggest that between 1986 and 1991 both the absolute and relative rates of deforestation had slowed since Sader and Joyce's (1988) estimates for 1977-1983. This decline in the rate of deforestation is supported by an independent estimate from the Food and Agriculture Organization of the United Nations, of 2.3% per year for the period from 1981 to 1990 (Whitmore 1997).

Much of the area deforested was converted to cattle pastures. Harrison (1991) found that from 1950 to 1984 in the 'frontier' regions of the country, where most deforestation occurred, there was a nearly 1:1 relationship between amount of forest lost and pasture gained. The cattle export market started in 1954 with exports of live animals, but soon switched to export of beef (Hall 1985). Government incentives encouraged the growth of the beef export market and by 1978 beef rated third of the primary export products, after coffee and bananas (Hall 1985). Between 1973 and 1984 the growth in area of pastures slowed in comparison with the previous period. By 1989 beef exports had dropped dramatically in response to falling prices (Lehmann 1992). In 1996 beef exports did not appear in the government statistics for principal export products; bananas, coffee and pineapple were listed as the top three exports (Ministerio de Economia Industria y Comercio 1996a).

The impact of the massive conversion of forest to pastures, and the closing of the colonization frontiers, prompted the start of forest protection policies in Costa Rica, starting with the Ley Forestal of 1969 (Hall 1985). During the 1970s and early 1980s a large proportion of forest reserves and protected areas existing today were declared (Centro Cientifico Tropical 1982). Tropical Science Center figures show 22% of the country to be in reserves and protected areas (Centro Cientifico Tropical 1982), and in 1992 Costa Rica was

---

1 Absolute rate is the area per year, expressed as a percentage of the total area; relative rate is the area per year, expressed as a percentage of the amount of cover existing at the start of the period in question.
recognized for its conservation policies by the United Nations Conference on the Environment (Nygren 1995). Subsequent forestry laws have attempted to control deforestation, and reduce the incentives to clear land. The most recent forestry law, passed in 1996, sets out new tax incentives for reforestation in the private sector (Diario Oficial 1996), and it remains to be seen what impact this will have on future land-uses.

THE LOCAL HISTORICAL SETTING: SARAPIQUÍ CANTON

The Sarapiquí region was one of the last settlement frontiers in Costa Rica. It was not until around 1950 that the area really started to be opened up for colonization. Prior to 1950 the region remained relatively isolated, and was occupied primarily by shifting agriculturists and some subsistence farmers.

A period of intensive colonization in the region from circa 1963 to 1973 contrasted with much of the rest of the country (Figure 3.1), which was experiencing migration back to the cities. This wave of colonization was in line with the start of development of banana plantations in the east of the canton in Río Frío in 1967, in addition to government incentives to develop the beef industry and the consequent boom in beef exports. The main result of this boom in the beef industry was the gradual accumulation of large ranches owned by a small proportion of the population (Augelli 1987; Pierce 1992b), many of whom were absentee owners (Butterfield 1994a). By 1973 Sarapiquí and the northern San Carlos plains were second only to the north Pacific lowlands in terms of their contribution to the nation's beef production (Hall 1985). Whereas most of the rest of the country was experiencing only marginal rates of conversion of forest to pasture during 1973 to 1984, the Provinces of Heredia and Limon saw large increases (Butterfield 1994a; Lehmann 1992). By 1983 over half the land area in Sarapiquí was under pasture (Pierce 1992a). Much of the improvements in access and services happened during the 1970s and 1980s (Butterfield 1994a).

In 1982 a Protection Zone linking Braulio Carrillo National Park (BCNP) with La Selva Biological Station was declared, forbidding any intensification of landuse within its boundary. In 1986 the Protection Zone was formally declared as an extension to BCNP (McDade and Hartshorn 1994). At about the same time, the agricultural frontier closed, meaning that
Figure 3.1. Human population of Costa Rica and Sarapiquí Canton: 1950-1983

Sources: Dirección General de Estadística y Censos, cited in Pierce 1982b; Ministerio de Economía Industria y Comercio 1986b
unclaimed land no longer existed in Costa Rica (Butterfield 1994a). Consequently colonization took the form of distribution of asentamientos by IDA (i.e. redistribution of private lands), orchestrated through organized squatter invasions, and resulting in a reduction in the average size of farms and a shift from extensive cattle ranching to subsistence agriculture and cash crops (Butterfield 1994a; Pierce 1992b). It was estimated that by 1983 38% of Sarapiquí comprised IDA farms, accounting for almost 50% of the population (Butterfield 1994a).

Agriculture has become prominent during the 1990s. Since the late 1980s the importance of agricultural exports as alternatives to beef grew in response to government subsidies (Lehmann 1992), and in 1990 Standard Fruit started to establish banana plantations along the Río Sucio to the north of Puerto Viejo (Montagnini 1994). In 1995 Sarapiquí's agricultural production comprised primarily bananas (61%), palm heart (15%), pineapple (9%), oranges (5%), and ornamental plants (3%) (Gobierno de Costa Rica 1996).

STUDY SITE

The study site is located in the northeastern Costa Rican province of Heredia where the foothills of the Central Volcanic mountain range meet the Caribbean coastal plain (Figure 1.2). Rivers drain northward into the Río Sarapiquí. Holdridge life zones in the study area include tropical wet forest in the northern lowlands of the study area, and premontane wet forest near Puerto Viejo (Hartshorn 1983).

Two major roads connect Puerto Viejo with San Jose. Several small communities exist along these routes outside the protected areas. La Selva Biological Station of the Organization for Tropical Studies (OTS) and the northern section of Braulio Carillo National Park lie within the study area. The elevation at La Selva rises from 35 meters above sea level at the north end of the property to 137 meters in the southwest (McDade and Hartshorn 1994). La Selva and Braulio Carrillo National Park together encompass an area of 47,000 hectares and make up part of the Cordillera Volcánica Central Biosphere Reserve. A protection zone, prohibiting any change in land-use, extends 300 meters on either side of the narrow extension between the main body of the park and La Selva (Schelhas 1991).
METHODS

Landscape patterns

Landscape patterns for the study site were examined using land-cover maps derived from aerial photographs for 1960, 1983, and 1992, and Landsat-TM data for 1986 and 1996 (see Chapter 2 for a description of the dataset). The classification scheme for the land-cover maps included forest, pasture, agricultural crops, and scrub\(^1\) (see Chapter 2 for a description of the classification scheme). The land-cover patterns were interpreted using land-cover information collected in the field during 1996 and 1997, which included spatially-referenced information on specific crops and conditions of pastures and forests.

Standard landscape and class indices were derived for each map in the time series using the FRAGSTATS program (Oregon State University, OR). Class indices included percentage of the landscape per patch type/class, number of patches\(^2\) per class, mean patch size per class, edge density, and total core area per class. The core area of a patch was defined as the area greater than 100 meters from the edge of the patch, which was based on the work of Laurance et al. (1997) who found that the greatest edge effects occurred within 100 meters of an edge in central Amazonian forests. The importance of edge effects in ecological functioning of forests has been well documented (e.g. see Laurance and Bierregaard 1997); thus, the core area was selected based on forest criteria rather than other land-cover types. The landscape indices examined are listed in Table 3.1, and were chosen to help describe both landscape composition (i.e. what the landscape comprises) and configuration (i.e. how the components of the landscape are arranged spatially). An explanation of Shannon’s Diversity Index is described in Chapter 5, section entitled ‘Common Landscape Indices’. The Interspersion and Juxtaposition Index (IJI) describes the interspersion of patch types (i.e. the distribution of patch-type adjacencies), and is defined as:

\(^1\) Scrub is an intermediate category between non-forest and forest, which is identifiable from the aerial photographs but was not reliably identified from the TM classifications.

\(^2\) A patch is a contiguous area (or polygon) representing a land-cover class.
Table 3.1. Landscape indices: general trends 1960-1996

<table>
<thead>
<tr>
<th>Index</th>
<th>Landscape</th>
</tr>
</thead>
<tbody>
<tr>
<td># patches</td>
<td>Increase</td>
</tr>
<tr>
<td>Mean patch size</td>
<td>Decrease</td>
</tr>
<tr>
<td>Edge density (edge length/area)</td>
<td>Increase</td>
</tr>
<tr>
<td>Total core area</td>
<td>Decrease</td>
</tr>
<tr>
<td># disjunct* core areas</td>
<td>Increase</td>
</tr>
<tr>
<td>Mean area per disjunct core</td>
<td>Decrease</td>
</tr>
<tr>
<td>Disjunct core area coefficient of variation</td>
<td>Increase</td>
</tr>
<tr>
<td>Core area % of landscape</td>
<td>Decrease</td>
</tr>
<tr>
<td>Mean core area % of patch</td>
<td>Increase to 1983, then decrease</td>
</tr>
<tr>
<td>Shannon's diversity index</td>
<td>Increase</td>
</tr>
<tr>
<td>Interspersion/Juxtaposition index</td>
<td>Increase to 1983, then decrease</td>
</tr>
</tbody>
</table>

*A single patch may contain several disjunct core areas*
\[
LJI = \frac{\sum_{i=1}^{m'} \sum_{k=1}^{m'} \left( \frac{e_{ik}}{E} \right) \ln \left( \frac{e_{ik}}{E} \right)}{\ln \left( \frac{1}{2} \left[ m'(m' - 1) \right] \right)} (100), \text{ where } e_{ik} = \text{total length of edge in landscape between patch types } i \text{ and } k; \ E = \text{total length of edge in landscape; and } m' = \text{number of patch types in the landscape (McGarigal and Marks 1995). The higher the } LJI \text{ value, the more interspersed the patch types (i.e. more equal adjacency of patch types to other patch types)(McGarigal and Marks 1995).}

Land-cover changes

Change analyses were conducted for the common extent (Figure 2.2) of all data layers using post-classification comparisons (overlays) for three periods: 1980 to 1983, 1983 to 1992, and 1986 to 1996. Note that the 1983 to 1992, and 1986 to 1996 periods overlap. Results from these two periods are presented separately to avoid making direct comparisons between data derived from Landsat-TM and aerial photograph interpretations, due to inherent differences in the data. Small polygons (less than 3 hectares) were eliminated from the resulting change maps to minimize the effects of rectification errors between the data layers and individual patch boundary errors. Patterns of change for each period were described and quantified using standard landscape and class indices.

Mean annual absolute and relative rates\(^1\) of change were calculated for each cover type. The relative rate refers the rate of change back to the amount of each category at the beginning of the period in question. Without the start of each period having some particular significance to the issue of land-cover change, the interpretation of these figures is difficult, however they do give some insight into the dynamics of change for the individual periods. The absolute rate is based on the percentage of the landscape by which the respective land-cover

\(^{1}\text{Absolute rate} = \frac{(T2-T1/\text{years})/\text{landscape area}}{\text{landscape area}} \times 100 \text{ where } T1 \text{ is the value at the start of the period, } T2 \text{ is the value at the end of the period. Relative rate} = \frac{(T2-T1/\text{years})/T1}{T1} \times 100 \text{ where } T1 \text{ is the value at the start of the period, } T2 \text{ is the value at the end of the period.}
category changed; this permits not only comparison of change through time for each category, but also across categories.

Road networks

To look for patterns of land-cover relating to improvements in transportation, the development of the road network from 1960 to 1992 was examined in relation to land-use and land-cover changes within that period. For each date (1960, 1983, and 1992) a distance image was generated (i.e., an image wherein the value of each pixel represented a distance in meters to the nearest road (Figure 3.2), as determined from the aerial photographs for each date). Where large rivers (Ríos Sucio, Puerto Viejo, and Sarapiquí) restricted access at points where bridges or ferry crossings did not exist in the year under consideration, the nearest road distances were likewise restricted to reflect actual access to all points. Roads known to exist outside the study area, but having an impact on the distance to nearest road within the study area, were included in generating the distance images. The distance images were recoded using 1-kilometer class intervals. Distances corresponding to land-cover categories for each date, and change categories occurring from 1960 to 1983, and 1983 to 1992, were extracted using matrix overlay analyses.

RESULTS

Landscape patterns

The study area remains a primarily forested environment (Figures 3.3 and 3.4). Non-forested areas in 1960 were generally confined close to roads and rivers (Figure 3.5). The first road connecting the region with San Jose, completed in the 1950s, followed the path of the Río Sarapiquí as far north as the town of Puerto Viejo, from where transport could continue by river to the Río San Juan. By 1960 a road connected Horquetas to Puerto Viejo, with a ferry-crossing over the Río Sarapiquí (Butterfield 1994a). Other roads built by 1960

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1 The 1986 and 1996 data were not included in this analysis because road networks were not reliably identifiable from the Landsat-TM images.

2 Analyses for change categories were done for common area extent. Road distance images corresponded to the final date of each period.
Figure 3.3. Old-growth forest canopy at La Selva Biological Station

Figure 3.4. View from La Selva, looking northwest over lower secondary forest
included the road into Magsasay, the location of a penal colony established by the government in the late 1950s (Butterfield 1994a), and the roads to Sardinal and around San Gerardo. Aside from the road into Magsasay, all other roads existing in 1960 were closely associated with the major rivers, where rich alluvial soils and gentle slopes provide the best locations for agricultural activities.

The initial pattern of clearing established by 1960 is still evident in recent years (figure 3.6): non-forested areas remain concentrated in the same areas as those cleared by 1960, with subsequent clearings expanding outward from these areas. The majority of areas to be deforested by 1996 had already in part been affected by 1983.

There was an overall increase in fragmentation and diversity of the landscape over time (Table 3.1). From 1960 to 1996 there was an increase in the number of patches, a reduction in mean patch size, a three-and-a-half-fold increase in total edge, and an increase from 20 to 50 percent of the landscape of areas lying within 100 meters of an edge. The mean core area of individual patches increased from 1960 to 1983, in accordance with the establishment of large areas of pastures, followed by a decline with their subsequent breakup. A relatively large increase in Shannon's Diversity Index from 1960 to 1983 reflected the change from a low diversity landscape dominated by forest, to a more even distribution of land-cover types. The diversity continued to increase only slightly thereafter, further reinforcing the idea that the pattern of land-cover had been well established by 1983. The Interspersion and Juxtaposition Index showed an increase from 1960 to 1983, which suggests a transition from an uneven spatial distribution of patches to a more even distribution. The index then decreased after 1983, which probably reflects the concentration of plantation agriculture in a few key areas.

i) Forest

Class indices are summarized in Table 3.2. After a dramatic decrease in the area of closed forest from 1960 to 1983, the relative area in forest remained approximately constant (Figure 3.7). By 1996, as a consequence of the continual breakup and conversion of large forest patches to other uses (Figures 3.8, 3.9, 3.10, and 3.11), 34% of forests lay within 100
Figure 3.6. Land-cover in Sarapiquí: 1986-1996
Table 3.2. Land-cover class statistics

<table>
<thead>
<tr>
<th></th>
<th>1960</th>
<th>Aerial photograph maps</th>
<th>1992</th>
<th>Landsat-TM classifications</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Full extent</td>
<td>Excl. PA</td>
<td>Full extent</td>
<td>Excl. PA</td>
</tr>
<tr>
<td>Pasture</td>
<td>8</td>
<td>11</td>
<td>29</td>
<td>35</td>
</tr>
<tr>
<td>% of landscape</td>
<td>55</td>
<td>55</td>
<td>82</td>
<td>72</td>
</tr>
<tr>
<td># patches</td>
<td>31</td>
<td>31</td>
<td>73</td>
<td>79</td>
</tr>
<tr>
<td>Mean patch size (ha)</td>
<td>190</td>
<td>190</td>
<td>262</td>
<td>254</td>
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<tr>
<td>Patch size CV (%)</td>
<td>7</td>
<td>9</td>
<td>20</td>
<td>22</td>
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<tr>
<td>Core area (%land)</td>
<td>2</td>
<td>3</td>
<td>12</td>
<td>14</td>
</tr>
<tr>
<td>Agriculture</td>
<td>0</td>
<td>1</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>% of landscape</td>
<td>8</td>
<td>7</td>
<td>25</td>
<td>23</td>
</tr>
<tr>
<td># patches</td>
<td>11</td>
<td>13</td>
<td>24</td>
<td>27</td>
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<td>Mean patch size (ha)</td>
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<td>183</td>
<td>183</td>
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<td>Patch size CV (%)</td>
<td>0</td>
<td>1</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>Core area (%land)</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Forest</td>
<td>88</td>
<td>85</td>
<td>59</td>
<td>52</td>
</tr>
<tr>
<td>% of landscape</td>
<td>24</td>
<td>28</td>
<td>44</td>
<td>55</td>
</tr>
<tr>
<td># patches</td>
<td>739</td>
<td>490</td>
<td>271</td>
<td>152</td>
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<td>Mean patch size (ha)</td>
<td>298</td>
<td>255</td>
<td>410</td>
<td>317</td>
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<tr>
<td>Patch size CV (%)</td>
<td>7</td>
<td>8</td>
<td>17</td>
<td>18</td>
</tr>
<tr>
<td>Core area (%land)</td>
<td>77</td>
<td>72</td>
<td>42</td>
<td>34</td>
</tr>
<tr>
<td>Scrub</td>
<td>3</td>
<td>4</td>
<td>9</td>
<td>9</td>
</tr>
<tr>
<td>% of landscape</td>
<td>68</td>
<td>69</td>
<td>114</td>
<td>100</td>
</tr>
<tr>
<td># patches</td>
<td>10</td>
<td>10</td>
<td>15</td>
<td>15</td>
</tr>
<tr>
<td>Mean patch size (ha)</td>
<td>118</td>
<td>119</td>
<td>229</td>
<td>240</td>
</tr>
<tr>
<td>Patch size CV (%)</td>
<td>5</td>
<td>6</td>
<td>11</td>
<td>11</td>
</tr>
<tr>
<td>Core area (%land)</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>2</td>
</tr>
</tbody>
</table>

Full extent = indices calculated over the full common area extent; Excl. PA = indices calculated excluding protected areas; CV = coefficient of variation.
Figure 3.7. Land-cover as a percentage of the landscape
Figure 3.8. Total area and core area by land-cover: 1960-1992 (source: aerial photograph interpretations)
Figure 3.9. Total area and core area by land-cover: 1986-1996 (source: Landest-TM data).
Figure 3.10. Mean patch size and number of patches: 1960-1992 (source: aerial photograph interpretations)
Figure 3.11. Mean patch size and number of patches: 1986-1996 (source: Landsat-TM data)
meters of a change in cover. When protected areas were excluded from the analyses (i.e. only those areas lying outside the forests protected within the La Selva/Braulio complex were considered) the area in forest still comprised greater than 50% of the landscape, but a higher proportion of those forests (48%) lay within 100 meters of an edge. The highest rate of decrease in forest area occurred during the 1960-1983 period (Table 3.3). The similarity between the absolute and relative rates of deforestation is indicative of the fact that the proportion of forest in the landscape has always been high.

ii) Pasture

A large increase in the area under pasture from 1960 to 1983, accompanied by an increase in mean patch size, was followed by subsequent declines in total area and mean patch sizes, and a dramatic increase in the number of patches (Figures 3.8, 3.9, 3.10, and 3.11). These statistics are consistent with the creation of large cattle ranches up to 1983, followed by their subsequent breakup. The absolute rate of decline of pastureland from 1983 to 1992 was the fastest of all cover types during that period (Table 3.3).

iii) Scrub

The intermediate scrub category showed a consistent increase in area, number of patches, mean patch size, edge density, and core area statistics through 1992, with patches scattered throughout much of the landscape and associated primarily with non-forest cover (Figures 3.8 and 3.10). The absolute rate of increase in the scrub category during 1983-1992 was almost as great as the rate of decrease of pasture (Table 3.3). This increase in the scrub component – an intermediate cover type – is consistent with the increasing amount of change and interchange from one land-cover type to another.

iv) Agricultural crops

The area under crops and plantation agriculture increased overall (Figures 3.8, 3.9, 3.10, and 3.11). Agriculture has been located primarily close to the original roads, beginning with experimental rice cultivation in the 1960s along the Río Puerto Viejo (Pierce 1992b). This was followed by establishment of citrus plantations in the San Gerardo and Sardinal vicinities, and African Oil Palm along the road north of La Virgen, between 1980 and 1983. The oil palm
Table 3.3. Mean annual percentage rates of land-cover change: 1960-1996

<table>
<thead>
<tr>
<th></th>
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<th></th>
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<tbody>
<tr>
<td>Forest</td>
<td>-1.43</td>
<td>-0.14</td>
<td>-0.39</td>
</tr>
<tr>
<td>Pasture</td>
<td>10.9</td>
<td>-1.98</td>
<td>-1.00</td>
</tr>
<tr>
<td>Crops</td>
<td>25.48</td>
<td>4.46</td>
<td>16.56</td>
</tr>
<tr>
<td>Scrub</td>
<td>6.33</td>
<td>5.44</td>
<td>-8.74</td>
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</table>

b) Absolute rates (%)

<table>
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</tr>
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<tbody>
<tr>
<td>Forest</td>
<td>-1.26</td>
<td>-0.08</td>
<td>-0.24</td>
</tr>
<tr>
<td>Pasture</td>
<td>0.92</td>
<td>-0.58</td>
<td>-0.34</td>
</tr>
<tr>
<td>Crops</td>
<td>0.11</td>
<td>0.13</td>
<td>0.40</td>
</tr>
<tr>
<td>Scrub</td>
<td>0.22</td>
<td>0.46</td>
<td>-0.10</td>
</tr>
</tbody>
</table>

c) Relative rates (%) of change in the landscape

<table>
<thead>
<tr>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>Percentage change per year</td>
<td>1.6</td>
<td>3.7</td>
<td>1.9</td>
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</tbody>
</table>
plantations were subsequently abandoned. By 1992, banana plantations had been established on the alluvial plains of the Ríos Sarapiquí and Sucio, and by 1996 much of the area around and south of Sardinal, and around San Gerardo was largely under pineapple plantations (Figure 3.12).

The absolute rate of increase in area of cropland increased over time; from 1986-1996 it comprised the fastest-growing land-cover category in the landscape (Table 3.3). The relative rate of increase of crops was rapid during 1960 to 1983, corresponding to the beginnings of agriculture in the region. The rate of increase of area of cropland slowed during 1983-1992, and then increased again from 1986 to 1996, as a result of rapid establishment of plantation agriculture starting in the 1990s.

Land-cover changes

At the landscape level most net change occurred from 1960 to 1983: 36% of the landscape underwent at least one change in land-cover during the 22 year period. However, when the length of each period is taken into account, it becomes apparent that the highest absolute rates of annual change occurred during the years 1983 to 1992 (Table 3.3).

i) 1960 to mid-1980s

From 1960 to 1983 conversion of forest to pasture was the dominant dynamic (Figure 3.13), with the mean patch size of areas converted being 50 hectares, compared with 10 and 13 hectares for later periods (Table 3.4). Also, a substantial amount of land changed from forest in 1960 to scrub cover in 1983. The beginnings of crops and plantation agriculture were evident, with approximately equal areas of forest and pasture having been converted to agriculture.

ii) Mid-1980s to mid-1990s

From the mid-1980s approximately equal proportions of forest had been lost and gained, primarily to and from pastures and scrub (Figure 3.13; Table 3.4). There are two

---

1 The 1986-1996 Landsat-TM data and the 1983-1992 aerial photograph data are overlapping periods: changes have been interpreted together.
Figure 3.12. Locations of agricultural plantations in 1996
Figure 3.13. Land-cover change dynamics
Table 3.4. Change class indices.

### a) 1960-1983

<table>
<thead>
<tr>
<th>Class</th>
<th>P-P</th>
<th>P-Ag</th>
<th>P-F</th>
<th>P-Sc</th>
<th>Ag-P</th>
<th>Ag-Ag</th>
<th>Ag-F</th>
<th>Ag-Sc</th>
<th>F-P</th>
<th>F-Ag</th>
<th>F-F</th>
<th>F-Sc</th>
<th>Sc-P</th>
<th>Sc-Ag</th>
<th>Sc-F</th>
<th>Sc-Sc</th>
</tr>
</thead>
<tbody>
<tr>
<td>% of landscape</td>
<td>5.46</td>
<td>1.81</td>
<td>0.4</td>
<td>1.09</td>
<td>0.14</td>
<td>0.09</td>
<td>0.15</td>
<td>0.03</td>
<td>22.07</td>
<td>1.1</td>
<td>57.95</td>
<td>6.72</td>
<td>1.91</td>
<td>0.25</td>
<td>0.49</td>
<td>0.56</td>
</tr>
<tr>
<td># patches</td>
<td>42</td>
<td>12</td>
<td>12</td>
<td>19</td>
<td>2</td>
<td>3</td>
<td>1</td>
<td>1</td>
<td>89</td>
<td>15</td>
<td>33</td>
<td>89</td>
<td>40</td>
<td>7</td>
<td>11</td>
<td>13</td>
</tr>
<tr>
<td>Mean patch size (ha)</td>
<td>26.27</td>
<td>27.05</td>
<td>6.66</td>
<td>11.56</td>
<td>14.26</td>
<td>5.98</td>
<td>29.41</td>
<td>6.89</td>
<td>50.09</td>
<td>14.76</td>
<td>354.71</td>
<td>15.24</td>
<td>9.63</td>
<td>7.17</td>
<td>9.06</td>
<td>8.69</td>
</tr>
<tr>
<td>Patch size CV %</td>
<td>152.87</td>
<td>154.65</td>
<td>86.73</td>
<td>92.59</td>
<td>56.24</td>
<td>24.7</td>
<td>0</td>
<td>0</td>
<td>238.57</td>
<td>74.48</td>
<td>356.07</td>
<td>165.95</td>
<td>94.99</td>
<td>44.19</td>
<td>62.13</td>
<td>62.76</td>
</tr>
</tbody>
</table>

### b) 1983-1992

<table>
<thead>
<tr>
<th>Class</th>
<th>P-P</th>
<th>P-Ag</th>
<th>P-F</th>
<th>P-Sc</th>
<th>Ag-P</th>
<th>Ag-Ag</th>
<th>Ag-F</th>
<th>Ag-Sc</th>
<th>F-P</th>
<th>F-Ag</th>
<th>F-F</th>
<th>F-Sc</th>
<th>Sc-P</th>
<th>Sc-Ag</th>
<th>Sc-F</th>
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<tbody>
<tr>
<td>% of landscape</td>
<td>16.69</td>
<td>3.47</td>
<td>4.69</td>
<td>4.52</td>
<td>1.23</td>
<td>0.55</td>
<td>0.71</td>
<td>0.63</td>
<td>4.87</td>
<td>0.2</td>
<td>48.44</td>
<td>5.77</td>
<td>1.84</td>
<td>0.06</td>
<td>5.23</td>
<td>1.23</td>
</tr>
<tr>
<td># patches</td>
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<td>15</td>
<td>91</td>
<td>75</td>
<td>15</td>
<td>5</td>
<td>10</td>
<td>12</td>
<td>94</td>
<td>5</td>
<td>44</td>
<td>62</td>
<td>34</td>
<td>2</td>
<td>64</td>
<td>27</td>
</tr>
<tr>
<td>Mean patch size (ha)</td>
<td>40.9</td>
<td>46.46</td>
<td>10.36</td>
<td>12.12</td>
<td>16.49</td>
<td>22.12</td>
<td>14.23</td>
<td>10.56</td>
<td>10.42</td>
<td>8.02</td>
<td>221.21</td>
<td>18.71</td>
<td>9.7</td>
<td>6.14</td>
<td>16.43</td>
<td>9.13</td>
</tr>
<tr>
<td>Patch size CV %</td>
<td>171.78</td>
<td>143.22</td>
<td>84.87</td>
<td>130.01</td>
<td>121.11</td>
<td>90.07</td>
<td>75.85</td>
<td>73.9</td>
<td>86.95</td>
<td>42.82</td>
<td>382.12</td>
<td>145.27</td>
<td>110.5</td>
<td>15.52</td>
<td>128.03</td>
<td>57.15</td>
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</table>

### c) 1986-1996

<table>
<thead>
<tr>
<th>Class</th>
<th>P-P</th>
<th>P-Ag</th>
<th>P-F</th>
<th>P-Sc</th>
<th>Ag-P</th>
<th>Ag-Ag</th>
<th>Ag-F</th>
<th>Ag-Sc</th>
<th>F-P</th>
<th>F-Ag</th>
<th>F-F</th>
<th>F-Sc</th>
<th>Sc-P</th>
<th>Sc-Ag</th>
<th>Sc-F</th>
<th>Sc-Sc</th>
</tr>
</thead>
<tbody>
<tr>
<td>% of landscape</td>
<td>5.34</td>
<td>1.3</td>
<td>0.35</td>
<td>0.04</td>
<td>0.37</td>
<td>1.52</td>
<td>0.05</td>
<td>0.03</td>
<td>0.73</td>
<td>0.03</td>
<td>36.67</td>
<td>0.11</td>
<td>0.11</td>
<td>0.09</td>
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</tr>
<tr>
<td># patches</td>
<td>81</td>
<td>21</td>
<td>92</td>
<td>1</td>
<td>7</td>
<td>1</td>
<td>5</td>
<td>1</td>
<td>102</td>
<td>1</td>
<td>60</td>
<td>9</td>
<td>16</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean patch size (ha)</td>
<td>55.88</td>
<td>51.12</td>
<td>12.85</td>
<td>7.07</td>
<td>24</td>
<td>298.6</td>
<td>5.34</td>
<td>6.29</td>
<td>13.45</td>
<td>5.49</td>
<td>180.06</td>
<td>8.26</td>
<td>7.05</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Patch size CV %</td>
<td>239.91</td>
<td>143.97</td>
<td>113.3</td>
<td>0</td>
<td>101.95</td>
<td>0</td>
<td>40.47</td>
<td>0</td>
<td>149.29</td>
<td>0</td>
<td>525.9</td>
<td>72.49</td>
<td>55.64</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

CV = coefficient of variation; P, pasture; Ag, agriculture; F, forest; Sc, scrub.
possible explanations for the creation of new pastures from forests, while in other areas pastures are being abandoned: they either represent replacement pastures in the face of reduced quality of grasses, or they represent an intermediate step in the conversion of forest to crops. This dynamic between the forests, pasture, and the intermediate scrub covers is disguised when considering only net area measurements of cover types, such as those provided by census data, and is important when considering the ecological and environmental roles of young versus old growth forests.

The forests converted to pastures were derived from a mixture of old growth or selectively-logged forests, and secondary forests. Since 1986 old growth forests have continued to be cut for pastures in patches scattered throughout the study site. Prominent among these areas were patches in the western and less steep part of the Cerros de Sardinal (southeast of Sardinal), and also patches between the Río Puerto Viejo and the eastern boundary of La Selva/Braulio. Forests in these areas represent some of the last remaining old-growth forest (Figure 3.14) existing close to the major roads, where topography is not prohibitive to agriculture.

The conversion of forest to agricultural uses within the study site, in contrast to conversion to pastures, has been negligible and isolated. However, looking at a larger area, the Landsat-TM data do show that expansion of the banana plantations on the Río Sucio plains between 1986 and 1996 accounted for approximately 1400 hectares of forest cut, those areas lying primarily outside the study area.

Deforestation (i.e. conversion of forest to another cover-type) occurring within the study site and outside the protection of the Braulio/La Selva complex represented 1.4% per year (of unprotected forests existing in 1986) from 1986 to 1996. Deforestation primarily occurred in areas of steep terrain, restricted access, or swamps — those being the locations where unprotected forest remained. The effects of logging were not apparent from these analyses; logging is selective and not readily distinguished in the aerial photographs or Landsat-TM images.
Areas not shaded white within the outlined study area represent areas classified as closed forest for all dates: 1960, 1983, 1986, 1992, and 1996.

Figure 3.14. Locations of old-growth forest
The impact of the declaration of the extension to Braulio Carillo National Park accounted for only 11% of the pastures abandoned to forests between 1986 and 1996, with the remaining 89% regenerating outside protected areas. Large patches regenerated between 1992 and 1996 to the west of the La Selva/Braulio complex, in areas of relatively poor access. Otherwise, regeneration occurred in patches scattered all over the landscape.

Pastures were also lost to agriculture (Figure 3.13); indeed, pastures provided the only significant source of new cropland within the study area. There was an increase in mean patch size and number of patches converted from pasture to agriculture throughout the time period, with a mean patch size of around 50 hectares during the 1986-1996 period (similar to the sizes of patches converted from forest to pasture in the 1960-83 period)(Table 3.4). Both bananas and pineapples were first introduced into the study site after 1986, with the majority of the bananas being planted between 1990 and 1992, although both crops continued to expand through 1997. Cultivation of small areas of ornamental plants likewise started in the early 1990s.

Road networks

The 1992 road network was more than five times as dense as that which existed in 1960 (Table 3.5). The density of the road network increased during 1960 to 1983 at a relative rate more than twice that of the 1983 to 1992 rate (12.4% vs. 5.1% per year). The same road from Puerto Viejo to San Jose via Vara Blanca, and a new road constructed in 1986 from San Jose via Braulio, following approximately the same route as the old road from Horquetas to Puerto Viejo, are the major thoroughfares today. The new road has cut the journey time from Puerto Viejo to San Jose to one-and-a-half hours compared with over two-and-a-half via the Vara Blanca route. Regular buses now serve the region daily via both routes. One obvious effect of the increase in density of the road network is the reduction in amount of land located at least two kilometers from roads.

1 But see above regarding deforestation for banana plantations outside the study site.

2 The latest information for the area was gathered in summer of 1997.
Table 3.5. Road network density and nearest distances: 1980-1992

<table>
<thead>
<tr>
<th></th>
<th>1980</th>
<th>1983</th>
<th>1992</th>
</tr>
</thead>
<tbody>
<tr>
<td>Road density (m/100ha)</td>
<td>258</td>
<td>987</td>
<td>1442</td>
</tr>
<tr>
<td>Relative rate of increase in</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>density (m/100ha) from</td>
<td></td>
<td>12.4</td>
<td>5.1</td>
</tr>
<tr>
<td>previous date (%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Maximum distance to nearest</td>
<td>12240</td>
<td>10489</td>
<td>2728</td>
</tr>
<tr>
<td>road (m)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean distance to nearest</td>
<td>2448</td>
<td>770</td>
<td>389</td>
</tr>
<tr>
<td>road (m)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Median distance to nearest</td>
<td>1842</td>
<td>399</td>
<td>229</td>
</tr>
<tr>
<td>road (m)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Modal distance to nearest</td>
<td>120</td>
<td>17</td>
<td>6</td>
</tr>
<tr>
<td>road (m)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard deviation (m)</td>
<td>2244</td>
<td>1131</td>
<td>454</td>
</tr>
</tbody>
</table>

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Land-cover was found to be highly significantly\(^1\) associated with distance to the nearest road for all dates (Figure 3.15). From 1980 to 1992 the majority of non-forest cover types were located primarily within one kilometer of a road: the individual chi-square contributions indicate pasture highly likely to be located within one kilometer of roads, whereas forest was associated with distances greater than one kilometer from roads\(^2\). In 1983 and 1992 crop patches were located within one kilometer of roads. In other words, agricultural crops and cattle ranches, land-uses that needed access to markets, were located mostly close to roads, whereas forests were found mostly at distances greater than one kilometer of a road; indeed, in 1992 agricultural crops were located only within one kilometer of a road.

The locations of areas that underwent change versus no-change from 1960 to 1983 and 1983 to 1992, likewise showed a highly statistically significant association\(^3\) with distance to roads (Figure 3.16). Areas that underwent change were mostly located within one kilometer of roads, although land-cover changes did occur at distances greater than three kilometers from roads during 1960 to 1983. This was due to the establishment of pastures along the east bank of the Río Sucio where roads had not been cut (presumably access was via river), and also an isolated field which was abandoned at the southern boundary of La Selva Biological Station. From 1983 to 1992 the only change that occurred at distances greater than three kilometers from a road was a result of forest regrowth inside Braulio Carrillo National Park.

DISCUSSION

Summary of results

By 1960 an era of widespread deforestation directly associated with the establishment of extensive cattle ranches (Figures 3.17 and 3.18) had begun in the study site, and continued

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\(^1\) Based on chi-square test for independence using contingency tables (P\textgreater;0.001).

\(^2\) Note: statistical results must be interpreted with caution due to the extremely high sample sizes (=pixels) in these analyses, which tend to return highly significant values. Also, the existence of spatial autocorrelation will affect results. These statistics were interpreted in terms of their relative values to one another.

\(^3\) Based on chi-square test for independence using contingency tables (P\textgreater;0.001).
Figure 3.15. Distribution of land-cover with respect to distance from nearest road
Figure 3.16. Distribution of change with respect to distance from nearest road.
Figure 3.17. Pasture: note the tree stumps lying on the ground which suggest the pasture is relatively young, and the scattered trees left to grow.

Figure 3.18. Low-lying pasture near Puerto Viejo with scattered trees.
until the mid-1980s. The data up to 1983 concur with the findings of others based on analyses of census data for the region (Butterfield 1994a; Pierce 1992b), indicating that the study site is representative of land-cover dynamics in Sarapiquí as a whole. The first decade of this era corresponded with a period of accelerated colonization in Sarapiquí. This occurred in response to the peak in the nation's population growth in the 1950s and the exhaustion of available lands in much of the rest of the country by the mid-1960s, making Sarapiquí one of the last remaining frontiers in Costa Rica (Butterfield 1994a; Hall 1985). The main reason for the delayed colonization of Sarapiquí was the difficulty of access either from the coasts, or from San Jose, which even today does not have guaranteed road access throughout the year through the mountainous stretches of the routes. By the mid-1980s the landscape had gone from one dominated by forest and contributing little to the nation's economy, to a more diverse and fragmented landscape, and an important beef producing region. Agricultural production in and around the study site included bananas, citrus, African Oil Palm, and Pejibaye palm for palm heart. Pejibaye was first planted on a large scale in the area in 1975, and represented the first commercial plantation for palm heart in Latin America (E. Fallas, pers. comm.).

In the mid-1980s there was a dramatic decrease in the rate of forest clearing and establishment of pastures, and a new era of change began. The declaration of the Protection Zone linking Braulio Carrillo National Park with La Selva Biological Station in 1982 effectively used up all available land for colonization, and coincided with the start of decline in the beef market. Although the total amount of forest in the landscape remained approximately constant from the mid-1980s to the early 1990s there was still clearing of old growth, selectively-logged, and secondary forests for new pastures, which was balanced by regeneration of secondary growth from areas previously in pasture. Expansion of agricultural areas all but ceased, and oil palm plantations were converted to pastures, probably in response to falling prices following the recession of 1979-1982 (Lehmann 1992).

After 1986 a renewed interest in agriculture initiated a new era whereby the breakup of large ranches was implemented not only by creation of small farms, but also through large-scale plantation enterprises. This renewed interest in agriculture coincided with government
incentives in the late 1980s to encourage diversification of the export economy (Lehmann 1992). Banana plantations of the Standard Fruit Company were established on the alluvial plains of the Río Sucio around 1990, and have continued to expand. Road and bridge improvements across the Río Sucio accompanied this activity. At approximately the same time pineapple plantations were established in the Sardinal and San Gerardo vicinities (Figure 3.19). Aside from the large-scale banana and pineapple enterprises, other prominent cash crops in and around the study site include citrus, palm heart, ornamental plants, and yuca (Figure 3.20). IDA farmers grow a mix of subsistence crops in addition to cash crops; improvements in the road network (Figure 3.21) facilitate the transport of cash crops to market. For example, farm-to-farm collection by a distributor of cut palm hearts, and their transportation to the processing plant, facilitate the small-farm production of palm heart (Figure 3.22). The study area exhibits a much more diverse pattern of crops grown for exports compared with the bananas and beef of the mid-1980s. In addition, tourism has become an important source of revenue, with ecotourists attracted to the various private reserves and Braulio Carrillo National Park.

The changing patterns of land-cover and land-use documented for the Sarapiquí region - the rapid deforestation and conversion to extensive cattle ranching, followed by gradual land-use intensification - are typical of other frontier regions in the lowland Central American and Amazonian tropics (Schelhas 1996). However, the forces driving these changes vary at local, national, and regional scales. Factors commonly cited as influencing changes in land-cover and land-use include population/colonization processes, accessibility (roads), and external factors such as government policies and export economies.

Colonization Projects

By 1995 IDA settlements in Sarapiquí occupied approximately 52,000 hectares and had settled a total of just over 3,400 families on 48 ranches (Gobierno de Costa Rica 1996). At the same time an additional 21 groups comprising 1,200 families were squatting on lands (Figure 3.23), waiting for IDA to purchase and distribute preliminary titles (Gobierno de Costa Rica 1996). Most settlements in Sarapiquí were officially purchased prior to 1985; since then
Figure 3.19. A pineapple plantation, with pasture in the background, near San Gerardo

Figure 3.20. Yuca stems ready for planting
Figure 3.21. The road bridge over the Río Sarapiquí at El Roble (east of La Guaria): roads have been found to be associated with land-cover change

Figure 3.22. Harvested palm heart waiting for collection by the road outside the farmer’s home
Figure 3.23. A squatters camp east of La Guaria: land redistribution takes place today through organized land invasions.
only 50 hectares have been acquired by IDA, despite the need for more land (regional IDA office, La Virgen, unpubl. data).

Most farms in the region employ a variety of land-uses, including cash crops (black pepper, yuca, pineapple, plantains), pastures, and more recently, reforestation projects (regional IDA office, La Virgen, unpubl. data). Approximately 80-90% of all small reforestation projects are carried out on IDA farms. These projects, aimed at IDA farmers, are being encouraged by the government through subsidies and provision of legal and technical help (P. Rojas, pers. comm.). In contrast with extensive cattle ranching where returns on land are low, the IDA farms are more intensive and more likely to be able to assign small areas for tree planting (Schelhas et al. 1997). Thus, the impact of the breakup of large cattle ranches, combined with government reforestation incentives, could result in an increase in the number of small, young forest patches existing within the landscape.

The spatial resolution of the Landsat-TM data, and hence the scale of the land-cover dataset, was not sufficient to isolate the small-scale farming and tree-planting activities on IDA farms. However, it is apparent that colonization projects (Figure 3.24) are associated with non-forested areas, and that the land-cover patterns are more fragmented than the larger ranches and plantation lands.

The initial pattern of land-use and road network

The initial pattern of land-use and structure of the road network established by 1960 have persisted to the present day. Patterns of forest clearing radiated out from locations centered on the road network, which initially followed the major rivers and rich alluvial soils. A strong association between the distribution of roads and land-cover was found. In 1992 all agricultural cropland lay within one kilometer of the nearest road, presumably driven by the need for transportation to carry cash crops to market. Forests were located primarily away from roads, in protected areas, or locations not favored for agriculture. Locations of land-cover change were also strongly associated with proximity to roads. These findings indicate the importance of local edaphic conditions and transportation/access in enabling the process.
Source: original maps, Instituto de Desarrollo Agrario (IDA), San Jose.

Figure 3.24. Location of colonization projects
of land-use intensification, first from forest to pasture, then pastures to plantation agriculture and cash crops on small IDA farms.

The relationship between roads and land-cover and land-use patterns at the national scale has been documented by Sader and Joyce (1988). The findings presented here demonstrate that even at local scales roads and landscape patterns are inextricably linked, regardless of the processes at work. Veldkamp et al. (1992) found a similar result when looking at the locations of roads and deforested areas in a site to the east of Sarapiquí. Elsewhere, Sader (1995; 1994) studied forest-clearing patterns in the Petén region of Guatemala and likewise found the existence of roads to be strongly related to patterns of forest clearing.

**Forces driving land-cover change**

The processes that shaped the pattern of land-use and land-cover changes in the Sarapiquí region since the 1960s have changed over time. The initial era of colonization was driven by the need for land as a result of population increase and pressure for land in the rest of Costa Rica (Hall 1985). A combination of factors can be attributed to the deforestation and the establishment of pastures that transpired. These include i) the availability of forest land and improvements in access to the region, ii) organized colonization and land tenure laws which facilitated the granting of title to land, and iii) the increase in the number of large ranches, which was driven by the boom in the beef export market, originally promoted by United States' interests (Augelli 1987), and encouraged through Costa Rican government incentives (see also Butterfield 1994a; Harrison 1991; Pierce 1992b).

From the early-1980s, alongside continuing colonization, the decline in beef exports combined with the closing of the agricultural frontier, lead to the breakup of large ranches. Continued colonization and establishment of small farms throughout the 1990s, in conjunction with government incentives to diversify the export economy with alternative crops, lead to increases in the area under crops and diversification of agricultural products. Large-scale plantation interests further promoted conversion of pastures to crops.
CONCLUSIONS

Driving forces of change

The three major forces driving land-cover and land-use change at work in the Sarapiquí region throughout the 1960 to 1996 period were colonization processes, infrastructure development, and changes in export markets. The closing of the settlement frontier in the mid-1980s, however, also played a keystone role in the patterns of change (Figure 3.25). These national-scale forces, working within the context of local factors such as roads, local edaphic conditions, and historical land-use patterns, lead to the present-day configuration of land-cover and land-use within the landscape.

The findings of this research suggest three factors which may provide potential predictors of future LUCC sites: i) road networks, examined within their historical context, ii) local physical environmental factors which indicate land suitability characteristics for specific land-uses, and iii) proximity to intensive land-uses and locations of recent land-use changes. Relatively simple spatial statistical models have been used as predictors of land-cover changes based on landscape information from periods just prior to those under analysis (Lambin 1997). A future line of research with this dataset would be to build a statistical model including as variables i) distance to the nearest road, ii) elevation and slope, or soils, and iii) distance to the nearest location of change that occurred between 1986 and 1996. Such a model would highlight areas of potential changes, which could then be further modeled using specific variables, including historic factors, depending on the type of change under examination. Although these models can predict future locations of change, the challenges ahead lie in predicting when changes will occur (Lambin 1997), and in integrating the driving forces of change in the models.

The importance of intra-regional studies of land-use changes has been emphasized by Moran et al. (1994) with respect to different parts of the Amazon. Studies investigating the spatial nature of LUCC for countries in Central America other than Costa Rica have been limited, and more landscape scale studies are needed to understand the processes of change occurring in the region.
Figure 3.25. Change in Sarapiquí: 1950 -1996
Methodology

The methodology used in this study demonstrated some of the uses and limitations of Landsat-TM data for characterizing land-cover, and land-cover changes. General limitations include i) the relatively recent (1982) start of Landsat-TM data collection, which means that for studies of historical land-cover alternative data sources are required, and ii) the lack of cloud-free images for tropical environments, which is based on the temporal resolution of the satellite. The use of aerial photographs in this study served to supplement the lack of available images, both historical and more current, and at the same time served as reference data for classifying the Landsat-TM data.

In this study the Landsat-TM data were classified using an unsupervised procedure to extract four general cover-types: forest, pasture, agriculture and scrub. This classification scheme was selected as a function of the spatial and spectral resolutions of the data, the ability of the unsupervised classification method to extract land-cover classes, and the scheme of the aerial photograph maps. In the mid-1980s this classification scheme would have been adequate to characterize the predominant changes occurring in the study site. However, it is apparent from changes that occurred in the study site in the 1990s that, although the land-cover changes associated with the larger-scale plantation enterprises were detected well, the finer-scale changes associated with mixed agriculture on IDA farms went undetected, despite comprising an important aspect of change within the landscape. Thus, the ability of these data to characterize present-day land-cover changes in the study site was dependent on the scale at which the individual changes were occurring. It should be noted, however, that the landscape fragmentation statistics did provide an indication of the increased degree of fragmentation that accompanied these changes. As landscapes in the tropics become more fragmented, and land-uses more intensive and diverse, there is a need for finer resolution remote sensing data (finer both spectrally and spatially). The timely launch of Landsat-7, with the collection of panchromatic 15-meter resolution data, may provide data capable of detecting such changes. A future study of this type would benefit from using a multi-scale approach, employing a combination of Landsat-TM data to extract more general land-cover
changes over a larger area, and taking advantage of the spatial patterns that can be detected, in combination with finer-resolution data to identify more detailed changes.

REFERENCES


CHAPTER 4
COMPARISON OF DIGITAL SPECTRAL PATTERN RECOGNITION
CHANGE-DETECTION METHODS

INTRODUCTION

An important application of satellite remote sensing is the detection and monitoring of land-cover and land-cover changes. Before the advent and development of commercial satellite sensors, aerial photographs were the primary data source for change-detection studies, and aerial photographs are still used for such research (e.g. Kadmon and Harari-Kremer 1999; Turner 1990). However, aerial photographs are expensive and often difficult to acquire, especially in remote areas. Improvements in satellite remote sensing, global positioning systems, and geographic information technologies in the past decade have vastly facilitated the collection of land-cover data and the integration of different data types, and this is reflected in the number of studies using satellite remote sensing data to detect land-cover and land-cover changes.

Success of research using satellite remote sensing for change-detection however, has been variable due to problems associated with image-processing techniques and interpretation of results. Many different strategies exist to compare digital satellite data from two or more dates for detecting change. Several authors have assessed performances and accuracies of these different image processing techniques (e.g. El-Raey, Nasr, and El-Hattab 1995; Howarth and Wickware 1981; Macleod and Congalton 1998; Martin and Howarth 1989; Mas 1999; Price, Pyke, and Mendes 1992; Siljestrom Ribed and Lopez 1995; Singh 1986). Others have investigated performances of data derived from different sensors to detect change (e.g. Bastin, Pickup, and Pearce 1995; Csaplovics 1992; Lozano-Garcia et al. 1995; Martin and Howarth 1989; Sader et al. 1989). However, the many different methods, data types, and environments investigated prevent extraction of generalized conclusions from much of this research (Estes, Stow, and Jensen 1982; Singh 1989). Exceptions include the studies by Singh (1986) and, more recently, Mas (1999), which quantitatively compared performances of change-detection algorithms using Landsat Multispectral Scanner (MSS).
data for detecting changes in a forested environment in northeastern India, and a coastal tropical environment in Mexico, respectively. Also, Macleod and Congalton (1998) compared different methods using Landsat Thematic Mapper (TM) data for detecting changes in submerged aquatic vegetation for a study site in the northeastern United States, and Fung (1990) compared methods using TM-data for a rural-urban environment in Ontario, Canada. The main conclusion to be drawn from results of these studies is that performances of different methods vary with environment (see also Singh 1989).

More research is needed investigating the responses of different environments and also specific change types (see Fung 1990) to change-detection algorithms. This paper compares some of the standard change-detection image processing techniques for a lowland tropical forested environment (i.e. the site in northeastern Costa Rica), which is experiencing a variety of changes typical of many lowland tropical environments. The requirement for more comparable local and regional land-cover and land-use change studies in tropical environments has been discussed in Chapter 1, and puts emphasis on the need for more detailed information on performances of different change-detection methods for the tropics. Through investigating standard techniques, results of this study are not only comparable with those of Singh (1986), Mas (1999), Macleod and Congalton (1998), and Fung (Fung 1990), but also provide information for promoting a standardized methodology for change-detection of specific change types in lowland tropical environments. This research expands on Singh's and Mas' work using Landsat-MSS data in lowland tropical environments to detect land-cover changes, through investigating the performance of the higher resolution Landsat-TM data for an area in the Caribbean lowlands of Costa Rica.

DIGITAL METHODS OF CHANGE-DETECTION

Changes in land cover are determined by analyzing multi-temporal data sets, whether analog or digital, to detect changes that have occurred between dates of data acquisition. Implementation of change-detection requires consideration of specific factors besides those necessary for single-date analyses (Table 4.1). Digital change-detection techniques are based on spectral and/or spatial pattern recognition through changes in radiance values, and
Table 4.1. General considerations in spectral pattern-recognition change detection

<table>
<thead>
<tr>
<th>Data selection</th>
<th>Data issues, transformation, and integration</th>
<th>Change analysis</th>
<th>Interpretation of change</th>
<th>Accuracy assessment</th>
</tr>
</thead>
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<tr>
<td>i) Type of change information required: hot-spots, specific change classes, classification scheme.</td>
<td>i) Georeferencing and rectification: accuracy of GCPs, conflation polygons.</td>
<td>i) Selection of change-detection algorithm.</td>
<td>i) Change classification scheme.</td>
<td>i) Sample vs. continuous assessment: sample size, sampling scheme.</td>
</tr>
<tr>
<td>iii) Resolutions: spatial, spectral, radiometric, temporal.</td>
<td>iii) Sensor differences: spatial, spectral, radiometric resolutions; sensor aberrations.</td>
<td>iii) Spectral distinctness of land-cover/land-cover change classes.</td>
<td>iii) Position errors: boundary errors from misregistrations, edge pixels, landscape fragmentation effects.</td>
<td>iii) Reference data accuracies.</td>
</tr>
<tr>
<td>iv) Reference data: sources, compatibility, timeliness.</td>
<td>iv) Computing resources</td>
<td>iv) Spectral distinction between classes and external noise</td>
<td>iv) Thematic errors</td>
<td>iv) Spatial autocorrelation.</td>
</tr>
<tr>
<td>v) Seasonality/anniversary dates.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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involve four steps: i) data transformation and image integration, ii) change analysis, iii) production of change maps, and iv) accuracy assessment.

Data transformation and image integration

Change-detection involves analysis and comparison of images taken at different times, sometimes from sensors with different spatial, spectral and radiometric resolutions. Data must be reconciled to compatible formats, and any noise and external effects in the images identified and removed. Accuracy of any change analysis that directly compares pixel values, or enhancements thereof, will depend on success of image integration.

Many pre-processing corrections are common to all or most procedures that use satellite data, such as removal of noise as a result of malfunctioning detectors, image edge-matching, and projection transformations. Of particular importance to change-detection are i) radiometric calibration of data values from different sensors, ii) correction of differences in sun elevation, earth-sun distance and atmospheric conditions, iii) normalization of differential effects of topography, and iv) resampling for differences in spatial and spectral resolution between sensors. Ideally the data are derived from the same sensor (Lillesand and Kiefer 1994), thereby eliminating problems arising from differences in radiometric, spatial, and spectral resolutions (points i) and iv)). Alternatively, data from different sensors may need converting to absolute radiance values (Lillesand and Kiefer 1994). Differences in sun angle, illumination and atmospheric conditions can be reconciled through radiometric normalization of the data using one of a variety of techniques, such as regressing pixel values of one image to a ‘master’ image based on unchanged pixels (Sabins 1978; Schott, Salvaggio, and Volchok 1988). Problems related to topographic effects are discussed by Colby and Keating (1998).

During single-image analyses it may not be necessary to precisely register an image, however where two or more images are to be analyzed based on corresponding pixel values it becomes of paramount importance to precisely co-register the images (Singh 1989). A variety of registration algorithms exist (see Fonseca and Manjunath 1996), the most common using least squares with resampling, such as nearest neighbor, bilinear interpolation, or cubic...
convolution. A general rule for accurate change-detection is to ensure registration to within $\frac{1}{4}$ to $\frac{1}{2}$ pixel (Lillesand and Kiefer 1994).

The accuracy of registration will depend on coordinate accuracy of control points and/or image coordinates (Clavet, Lasserre, and Poulion 1993; Cook and Pinder 1996). Improved accuracies and lowered costs of using the global positioning system (GPS) are promoting increasing use of this technology for ground control for registration. A common problem in registration is the occurrence of small boundary position errors resulting in conflation polygons (Aronoff 1991), which should not be mistaken for areas of change in subsequent analyses.

Change analyses

Spectral pattern-recognition change-detection techniques use one or more of enhancement, comparison, classification, and differencing/subtraction algorithms. The most commonly-used methods for change-detection using satellite data include postclassification comparison (Figure 4.1b), direct multi-date classification, image differencing techniques (with e.g. univariate bands, principal components, image ratioing (i.e. Normalized Difference Vegetation Index), and image regression)(Figure 4.1a), image ratioing, change vector analysis, and multi-date principal components analysis (MPCA)(Table 4.2). Descriptions of these methods are available in various sources such as Lillesand and Kiefer (1994), and Singh (1989). Change vector analysis is described in detail by Johnson and Kasischke (1998), and Fung and LeDrew describe the use of principal components analysis for change detection (Fung and LeDrew 1987). Selection of a change-detection method will depend on the purpose of the analysis, the availability and type of data, and computing resources.

The different change-detection strategies produce different types of results (Table 4.2). The classification techniques produce change maps of different change categories, that is, they give 'from-to' change class information. These techniques require knowledge of the study area in order to label the categories, whether for direct multi-date classification, or separate classification of the individual dates prior to postclassification comparison.
a) Image differencing

Input data time \(_1\)

\[\text{Input data time}_2\]

\[\text{Differencing image}\]

\[\text{Calculate threshold} \rightarrow \text{Rcode} \rightarrow \text{Change map}\]

\[\text{(two classes: change or no-change)}\]

b) Postclassification comparison

\[\text{Input data time}_1\]

\[\text{Input data time}_2\]

\[\text{Classification}\]

\[\text{Land-cover time}_1\]

\[\text{Land-cover time}_2\]

\[\text{Overlay}\]

\[\text{Land-cover change map}\]

\[\text{('from-to' change classes)}\]

Figure 4.1. Schematics showing image differencing and postclassification comparison
<table>
<thead>
<tr>
<th>Method</th>
<th>Options</th>
<th>Description</th>
<th>Outcome</th>
</tr>
</thead>
<tbody>
<tr>
<td>Postclassification comparison</td>
<td>Unsupervised classification, supervised classification</td>
<td>Overlay separate classifications of images taken at different times resulting in a change classification</td>
<td>From-to change classes</td>
</tr>
<tr>
<td>Univariate image differencing</td>
<td>Any band</td>
<td>Subtract pixel values of time(_1) from values of time(_2), and interpret using a change/no-change threshold</td>
<td>Change/no-change classes</td>
</tr>
<tr>
<td>Enhanced image differencing</td>
<td>Data transformations (e.g. filters, principal components) Ratio indices (e.g. NDVI)</td>
<td>Conduct image differencing on enhanced data layers from time(_1) and time(_2)</td>
<td>Change/no-change classes</td>
</tr>
<tr>
<td>Image ratioing</td>
<td>Band ratios, Index ratios</td>
<td>Calculate the ratio of bands or indices of time(_1) to time(_2), and interpret using a change/no-change threshold</td>
<td>Change/no-change classes</td>
</tr>
<tr>
<td>Direct multi-date classification</td>
<td>Unsupervised classification, supervised classification</td>
<td>Combine bands from time(_1) and time(_2) in a single image, and classify generating a change classification</td>
<td>From-to change classes</td>
</tr>
<tr>
<td>Multidate principal components analysis</td>
<td>Unstandardized PCA Standardized PCA Selective PCA</td>
<td>Combine bands from time(_1) and time(_2) in a single image, and calculate principal components. Interpret using a change/no-change threshold</td>
<td>Change/no-change classes</td>
</tr>
<tr>
<td>Change vector analysis</td>
<td>Enhancements/transforms</td>
<td>Calculate total spectral change magnitude and direction between time(_1) and time(_2). Interpret magnitude using a change/no-change threshold</td>
<td>Change/no-change classes with direction of change information</td>
</tr>
</tbody>
</table>
The differencing and ratiocing techniques, on the other hand, do not require a priori or a posteriori knowledge of the study area in order to extract potential change hot-spots, but provide only ‘change’ and ‘no-change’ information. If knowledge of the site is available and more detailed change information is required, however, it is possible to classify those pixels identified as having changed using a binary masking and classification technique (e.g. Mas 1999).

The use of principal components analysis in change detection, and change vector analysis, are conceptually more complex than the classification and differencing methods. Principal components need to be evaluated with care, and because the technique is scene-dependent, the proportion of change in the study area must be small compared with the area of no-change (Fung and LeDrew 1987). The use of non-standardized versus standardized components also requires consideration based on the characteristics of the data (Fung and LeDrew 1987). Change vector analysis generates information concerning the length and direction of spectral changes, which potentially provides more information about areas of change than the differencing algorithms.

Various techniques circumvent some of the image integration issues described above. For instance, where atmospheric and radiation differences between images cannot be corrected using pre-processing techniques, postclassification comparison may be considered most suitable because the independent classification of images minimizes such differences (Singh 1989). This method is also useful where different data types are used in analysis, such as aerial photographs and satellite imagery, or where radiometric calibration is not possible (Massart, Petillon, and Wolff 1995). Alternatively, MPCA can separate atmospheric and radiation differences and noise into the first principal component, while real changes in land cover are represented in the minor components (Singh 1989). Topographic effects and normalized differences in irradiance can be corrected using ratio image differencing whereby a ratio index, such as a vegetation index, is used in the differencing analysis (Singh 1986). Various indices such as ratio vegetation index, NDVI, and transformed vegetation index, exist.
With these spectral pattern-recognition techniques spectral changes resulting from land-cover changes must be large with respect to changes caused by external factors, such as atmospheric effects, sensor differences, and differences in sun angle and season. In addition, some techniques such as direct multi-date classification and change vector analysis, are more sensitive to the degree of spectral distinctness between change classes (Lillesand and Kiefer 1994).

PCA with image differencing or image ratioing is useful for reducing redundancy of information (e.g. Estes, Stow, and Jensen 1982; Singh 1986). Another use of PCA is to apply it to the results of direct multi-date classification to reduce the many classes with redundancy that this technique produces (Singh 1989).

Results and interpretation of changes

When interpreting changes it must be remembered that change-detection techniques identify changes between two discrete points in time, and that any intermediate changes occurring between those points will not be documented, although they may constitute a valid component of the change process. Thus, suitable temporal scale is key to success of change detection. Likewise, suitability of spatial resolution of the sensor must be confirmed for the purpose in hand (Estes, Stow, and Jensen 1982); if the spatial resolution is too coarse then there is a danger of identifying contiguous areas of change that are too large.

i) Classification methods

The resolution of a change classification scheme is determined by the spectral distinctness of change classes for direct multi-date classifications, and the original land-cover classifications for postclassification comparison. One advantage of methods employing classification is that they can be tailored to only treating change classes of interest (Massart, Petillon, and Wolff 1995).

Uncertain class boundaries are a problem with classification techniques, and will affect change results. These uncertainties arise from a combination of misregistration errors, unsharp/unclear boundaries on the ground, and problems in classification of mixed or edge-pixels. The precision with which boundaries can be determined on the ground will determine
the maximum accuracy level possible in the corresponding change map. Some boundaries can be more difficult to define than others on the ground, such as transitions across different vegetation types. Even within the same classification, ability to define boundaries between different classes may vary. This situation becomes more complex when dealing with changes between classes of different boundary characteristics. Consequently it seems logical that as landscapes become more fragmented, accuracy will decline as a result of boundary uncertainties. Edwards and Lowell (1996) provide a good discussion of boundary uncertainties.

ii) Differencing and ratioing methods

With image differencing and image ratioing the change results will depend on the chosen thresholds of change. Selection of change/no-change thresholds is somewhat arbitrary. Class boundaries are generally chosen based on band statistics. For example, in image differencing a 'differenced' distribution of pixel values is generated which approximates a normal curve, with change pixels lying in the tails of the distribution, and no-change values lying close to zero (Singh 1989). The change threshold is generally chosen as a function of the standard deviation. In image ratioing the ratio of digital numbers are calculated from two images, resulting in a new image with pixel values close to one for areas of no-change, and higher or lower numbers for areas of change (Lillesand and Kiefer 1994). Again, a threshold value must be selected to classify change/no-change areas.

Accuracy assessment

The final step in change-detection is assessment of the accuracy of the resulting change information. It is only since the early 1980s that research has focussed on methods of assessing accuracy of single-date satellite-derived classifications, which have been adopted for change-detection assessments. Knowledge of the accuracy, and the limitations, of data provided by remote sensing methods is increasingly important given the widespread use and ever-increasing complexity of remote sensing methods being used. Congalton (1991) and Congalton and Green (1999) provide excellent treatments of assessing classification accuracies with remote sensing data, including discussions on sampling schemes, sample
sizes, and spatial autocorrelation. The purpose of an accuracy assessment is to ensure that
the required accuracy is being attained, and if necessary, to revise classification schemes to
meet the accuracy requirements (Congalton and Green 1999). Classification accuracy
assessments are based on contingency tables (error matrices) comparing classified with
reference data. A method of presenting results specifically for change-detection error
matrices was recently described by Macleod and Congalton (1998).

Any assessment depends on the quality of the reference data. Affordable GPS can
provide sub-meter ground control point (GCP) position accuracies using differential
corrections which are suitable for most satellite remote sensing land-cover studies using
Landsat or SPOT (Système Pour l’Observation de la Terre) data. Indeed, Cook and Pinder
(1996) suggest that GCP accuracies better than 4 m are not required because the
_corresponding pixel coordinates cannot be measured with greater accuracy (at least with
Landsat-TM and SPOT data). Performance of GPS however, varies depending on the
environment (Deckert and Bolstad 1996). In closed forests, for example, the ability to record
positions may be reduced due to signal obstruction through dense canopies.

Because the emphasis in change-detection is on events that happened some time in
the past, reference data are often derived from aerial photograph interpretations, old maps,
and other historical sources. Ideally the accuracy of the reference data should be known,
however, there is often no way to assess these data.

SATELLITE REMOTE SENSING OF LOWLAND TROPICAL ENVIRONMENTS

Concern about global effects of deforestation, biomass burning, and population
increases in the tropics has meant that research with satellite remote sensing in the tropics
has increased in recent years (Brondizio et al. 1996), leading to a better understanding of
responses of tropical environments to remote sensing. Historically, researchers working with
single-date imagery reported poor results in distinguishing between types/ages of tropical
forests at local levels using Landsat-MSS and NOAA’s Advanced Very High Resolution
Radiometer (AVHRR) data (Brondizio et al. 1996). The higher resolution Landsat-TM data,
however, have been found to be useful in distinguishing different tropical vegetation types

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(e.g. Adams et al. 1995; Brondizio et al. 1996; Skole and Tucker 1993; Steininger 1996). Some authors have had mixed results, for example Sader et al. (1989) found that NDVI with Landsat-TM were not capable of predicting forest successional age, and Massart et al. (1995) found that in Zaire evergreen forest was the only vegetation type distinguishable from other vegetation types including savanna, woodland and fields. Other findings show that multi-date analyses give good results (Lambin 1996; Lucas et al. 1993), especially when combined with detailed ground and ecological data (Brondizio et al. 1996), and Sader (1995) concluded that forest types and forest change are "highly detectable" using multi-temporal remote sensing.

Problems associated with detecting land-cover and land-cover changes in lowland tropical environments using satellite remote sensing arise from the difficulty in distinguishing between tropical vegetation types, which is rooted in the complexity and structure of tropical vegetation communities. High species richness and associated lack of dominance of tropical vegetation types, combined with scant knowledge of tree phenologies, provide few clues or detectable patterns from satellite data. This is further compounded by weak seasonal patterns in many parts of the lowland tropics, which prevent use of seasonal differences in distinguishing vegetation types. However, even weak seasonal changes may affect results of change-detection, and Lambin (1996) warns that it is important to filter out these effects, which may be greater than longer-term changes.

Increased landscape fragmentation is a usual consequence of development in the tropics, as large areas of land become deforested and given over to different land uses. Thus, studies in the tropics looking at changes over several years or decades will need to consider changing landscape characteristics when assessing accuracies of change analyses. Such increased fragmentation will affect boundary errors as described above.

Additional problems associated with remote sensing of tropical environments include i) the scarcity of cloud-free data, which makes the use of anniversary dates sometimes impossible (Mas 1999), ii) the difficulty in obtaining historic reference data of known accuracy, and iii) the difficulty in obtaining ground reference data due to limited access.
PURPOSE OF THIS RESEARCH

The objective of this study was to identify which method(s) reliably detect land-cover changes in the study area in northeastern Costa Rica, through evaluating the performance of selected remote sensing image-processing techniques using Landsat-TM data. The methods evaluated were postclassification comparison, and image differencing for the time period 1986 to 1996. These techniques were selected because i) they include both classification and differencing algorithms, ii) they have been investigated in similar studies but with different sensor data and/or in different environments by Singh (1986), Mas (1999), Madeod and Congalton (1998), and Fung (1990), and iii) they represent standard, conceptually simple techniques. The enhancements investigated with differencing included NDVI, Tasseled Cap and PCA. The NDVI and Tasseled Cap were selected because the study area is primarily vegetated, and these indices/transforms are designed for discriminating vegetation. PCA was selected to determine if there was any underlying change information in the images that was not detected using univariate band differencing and vegetation transform differencing. Results of these methods were compared with change maps compiled from existing aerial photography, in combination with field data and auxiliary information.

METHODS

Data Sources

Landsat-TM data from two dates, 1986 and 1996, were used for these analyses (see Table 2.1). Both images were recorded by the same Thematic Mapper sensor on board Landsat 5.

Reference data for use in classification and accuracy assessments were derived from a variety of sources. The 1986 data were referenced using the 1983 and 1992 land-cover maps derived from aerial photographs described in Chapter 2, in combination with a color composite display of the 1986 image. The use of the 1983 and 1992 land-cover maps in conjunction with the display of the image allowed temporal logic to be used in interpreting areas that had changed between 1983 and 1986. The 1996 data were referenced using the GPS ground-reference data gathered in July and August 1997, in combination with color
composite displays of the 1996 image and the 1997 Landsat-TM image of the area (Table 2.1). Similarly, temporal logic was applied in interpreting areas that had changed since the 1996 image was recorded and the collection of ground reference data in 1997.

In addition to these reference sources, the map resulting from the 1986-1996 overlay analyses described in Chapter 3 was used as a 'reference classification' for visual comparisons of locations of change, and for aiding in selection of the reference sample for accuracy assessments (see below). This reference classification was derived from intersecting unsupervised classifications of 1986 and 1996 land-cover, which had been edited based on reference data from the aerial photograph interpretations, yielding overall accuracies 85% and 89%, with Kappa coefficients of 0.79 and 0.83, respectively (Figure 4.2).

Study area

A subset of the study site, comprising 107168 pixels (8705 ha), was selected based on three cloud-free areas on the 1996 Landsat-TM image (Figure 4.3). Thirteen of the potential sixteen change classes (based on the reference classification)(Table 4.3) were represented in the subset area, and seven of these classes encompassed an area of greater than 100 hectares. The other six classes were not well represented in the study area.

Discussion of the analyses will be primarily restricted to the seven well-represented classes.

Landsat-TM data pre-processing

Image pre-processing steps, including the generation of initial scene subsets, georeferencing and rectification procedures, radiometric normalization of the 1996 and 1986 images, and removal of clouds and cloud shadows, are fully described in Chapter 2. Important considerations for these analyses were accurate rectification to within 0.5 pixel of the two images, and normalization of the data values.

Preparation of data layers

i) Postclassification comparison

Unsupervised classifications of the 1986 and 1996 images were generated using 100 initial classes as described in Chapter 2. The classifications were filtered using a 3x3 window majority filter to eliminate speckling. The resulting image files were subsequently vectorized,
Figure 4.2. Land-cover change map from 1986 to 1996, derived from Landsat-TM data using aerial photographs as reference.

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Figure 4.3. Location of substudy areas
Table 4.3. Class areas based on the reference classification for the subset area

<table>
<thead>
<tr>
<th>Change class</th>
<th>Number of pixels</th>
<th>Area (hectares)</th>
</tr>
</thead>
<tbody>
<tr>
<td>P-P</td>
<td>30770</td>
<td>2499</td>
</tr>
<tr>
<td>Ag-Ag</td>
<td>3639</td>
<td>296</td>
</tr>
<tr>
<td>F-F</td>
<td>43488</td>
<td>3532</td>
</tr>
<tr>
<td>*Sc-Sc</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>P-Ag</td>
<td>10163</td>
<td>825</td>
</tr>
<tr>
<td>P-F</td>
<td>7178</td>
<td>583</td>
</tr>
<tr>
<td>*P-Sc</td>
<td>7</td>
<td>0.6</td>
</tr>
<tr>
<td>Ag-P</td>
<td>1865</td>
<td>151</td>
</tr>
<tr>
<td>*Ag-F</td>
<td>326</td>
<td>26</td>
</tr>
<tr>
<td>*Ag-Sc</td>
<td>74</td>
<td>6</td>
</tr>
<tr>
<td>F-P</td>
<td>6585</td>
<td>535</td>
</tr>
<tr>
<td>*F-Ag</td>
<td>67</td>
<td>5</td>
</tr>
<tr>
<td>*F-Sc</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>*Sc-P</td>
<td>431</td>
<td>35</td>
</tr>
<tr>
<td>*Sc-Ag</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>*Sc-F</td>
<td>1226</td>
<td>100</td>
</tr>
</tbody>
</table>

P, pasture; Ag, agriculture; F, forest; Sc, scrub.

* Classes comprising ≤ 100 ha in the reference classification.
and minimum mapping units of 3 hectares were applied. The resulting unedited classifications were used for this analysis (as opposed to the corrected/edited 'reference' classifications used for the change analyses in Chapter 3).

ii) Image differencing

The Normalized Difference Vegetation Index (NDVI), Tasseled Cap transformation, and non-standardized principal components, were calculated for the radiometrically-normalized 1986 and 1996 data for the common area extent of the time-series dataset. The common area extent was chosen to provide a realistic range of data values, as opposed to the small area of the subset analyses, for the scene-dependent principal components analysis.

NDVI contrasts the near-infrared and visible bands, and is widely used for detection of healthy vegetation, or 'greenness', based on vegetation reflectances that are high in the near-infrared portion of the spectrum, and low in the visible wavelengths:

\[
NDVI = \frac{Band4(NIR) - Band3(red)}{Band4(NIR) + Band3(red)}
\]

The Tasseled Cap transformation uses a set of linear combinations to rotate data in spectral space along one of several axes designed for vegetation studies (Crist and Cicone 1984; ERDAS 1995). The original transformation, described three axes: brightness incorporates reflectances of all bands and is related to soil brightness, greenness is similar to NDVI in contrasting visible and near-infrared bands, and wetness is related to soil and canopy moisture (Lillesand and Kiefer 1994) and is related primarily to the mid-infrared band 5 and 7 (Crist and Cicone 1984).

Principal components differencing will only work if the components contain similar information, which requires that the proportion of change in the study area be small (Fung and LeDrew 1987). The eigen matrices (Appendix A) for the non-standardized components demonstrated that the components are showing the same information for both dates, thereby justifying the use of separate computation of non-standardized principal components with differencing as a valid method to test.
Change Analyses

i) Postclassification Comparison

The classified vector layers were overlaid (intersected) and polygons less than 3 hectares, resulting from boundary errors and small change fragments, were eliminated.

ii) Image differencing

Image differencing was conducted through subtracting the prepared data layers of the 1986 data from the 1996 data. The resulting files were re-scaled to unsigned 8-bit files using a minimum/maximum stretch in IMAGINE. The minimum/maximum stretch was selected rather than a standard deviation stretch because in change-detection the pixel values at the tail ends of the distribution are of interest in that they represent change. The re-scaled 8-bit files permitted easy viewing and later re-coding of the files.

All difference bands/components and frequency histograms were examined visually. A common threshold of one standard deviation was selected for the change/no-change classes, through visual assessment of different standard deviations in conjunction with color composites of the Landsat-TM images. This visual evaluation was supported by comprehensive quantitative experiments by Fung and Ledrew (1988), who found the optimal threshold based on the highest Kappa coefficient to be 1.0 for three change-detection algorithms, and 0.9 and 1.1 for two others. The selection of a common standard deviation threshold was based on the desire to standardize the methodology, and was possible because the data were normally or near-normally distributed. Change/no-change classes using one standard deviation thresholds were visually assessed for each band/component, and the most promising bands in terms of performance based on visual evaluations, were selected and re-coded to change and no-change classes (Table 4.4). No attempt was made to assign 'from-to' identifiers to the final change classifications because the purpose here was to evaluate how well these different methods detected change, and any further processing could have introduced uncertainties during assessment of the results. The re-coded change/no-change maps were filtered using a 3x3 window majority filter to eliminate speckling.
Table 4.4. Standard deviation change thresholds used in image differencing

<table>
<thead>
<tr>
<th>Input layer</th>
<th>Mean – 1 SD (a)</th>
<th>Mean</th>
<th>Mean + 1 SD (b)</th>
</tr>
</thead>
<tbody>
<tr>
<td>TM band 2 differencing</td>
<td>178</td>
<td>202</td>
<td>226</td>
</tr>
<tr>
<td>TM band 3 differencing</td>
<td>186</td>
<td>211</td>
<td>238</td>
</tr>
<tr>
<td>TM band 5 differencing</td>
<td>129</td>
<td>162</td>
<td>195</td>
</tr>
<tr>
<td>TM band 7 differencing</td>
<td>148</td>
<td>177</td>
<td>205</td>
</tr>
<tr>
<td>NDVI differencing</td>
<td>78</td>
<td>104</td>
<td>129</td>
</tr>
<tr>
<td>PCA component 1 differencing</td>
<td>123</td>
<td>152</td>
<td>181</td>
</tr>
<tr>
<td>PCA component 2 differencing</td>
<td>117</td>
<td>149</td>
<td>180</td>
</tr>
<tr>
<td>Tasselled Cap transform 1 differencing</td>
<td>136</td>
<td>163</td>
<td>190</td>
</tr>
<tr>
<td>Tasselled Cap transform 2 differencing</td>
<td>67</td>
<td>94</td>
<td>121</td>
</tr>
<tr>
<td>Tasselled Cap transform 3 differencing</td>
<td>58</td>
<td>85</td>
<td>112</td>
</tr>
</tbody>
</table>

SD = Standard deviation; values < a represent change; values ≥ a and ≤ b represent no-change; values > b represent change.
Accuracy assessments

i) Contingency tables and Kappa statistics

The performances of the different change-detection methods were assessed using standard contingency tables. Accuracy statistics extracted included overall accuracy (%) for each method (this provides information concerning the diagonal (correctly classified) elements of the matrix only), and user's & producer's accuracies per category.

The Kappa coefficient of agreement ($k_{hat}$) was calculated for each method using the following equation from Hudson (1987):

$$
\hat{k} = \frac{\theta_1 - \theta_2}{1 - \theta_2}, \text{ where } \theta_1 = \sum_{i=1}^{r} \frac{x_{ii}}{N} \text{ and } \theta_2 = \sum_{i=1}^{r} \frac{x_{ii}x_{ai}}{N^2}
$$

and $r$ = number of rows/columns in the error matrix, $N$ = total number of samples, $x_{ii}$ = cell value in row $i$, column $i$ of the error matrix, $x_{ii}$ = summation of row $i$, and $x_{ai}$ = summation of column $i$. This statistic, unlike overall accuracy, incorporates information from the diagonal and off-diagonal (incorrectly classified) elements of the matrix, and is commonly the preferred measure of overall accuracy (Congalton 1991).

Z-scores based on the approximate large-sample variance of Kappa for each matrix were calculated to test for differences from a random result.

a) Large-sample variance, from Hudson (1987):

$$
\hat{\sigma}^2[\hat{k}] = \frac{1}{N} \left[ \frac{\theta_1(1-\theta_1)}{(1-\theta_2)^2} + \frac{2(1-\theta_1)(2\theta_1\theta_2-\theta_3)}{(1-\theta_2)^3} + \frac{(1-\theta_1)^2(\theta_1 - 4\theta_2^2)}{(1-\theta_2)^4} \right].
$$

where $\theta_1 = \sum_{i=1}^{r} \frac{x_{ii}}{N}$, $\theta_2 = \sum_{i=1}^{r} \frac{x_{ii}x_{ai}}{N^2}$, $\theta_3 = \sum_{i=1}^{r} \frac{x_{ii}(x_{ii} + x_{ai})}{N^2}$, and $\theta_4 = \sum_{i=1}^{r} \frac{x_{ij}(x_{ij} + x_{ai})}{N}$.

for $x_{ij}$ = cell value in row $i$, column $j$ of the error matrix, $x_{ij}$ = summation of row $j$, and $x_{ai}$ = summation of column $i$.

b) Z-score:

$$
Z \approx \frac{\hat{k}}{\sqrt{\hat{\sigma}^2}}
$$
Z-scores for pairwise comparison of matrices based on Kappa analysis to test for statistical differences between matrices were calculated as follows (from Congalton (1983)):

\[ Z \approx \frac{\hat{\kappa}_1 - \hat{\kappa}_2}{\sqrt{\sigma_1^2 + \sigma_2^2}} \]

The error matrices were constructed using a sample of points as opposed to continuous pixel-to-pixel assessments. Although continuous assessments are generally considered superior to sampling, errors would have been introduced as a result of i) boundary errors in the reference classification, ii) the three hectare minimum mapping unit of the reference classification, and iii) errors in the reference classification itself. Instead, a sample was selected which permitted avoidance of edges, spurious pixels, and careful interpretation of each sample point using all reference information at hand.

A stratified random sampling scheme was used for selection of the reference sample. Whereas the only sampling scheme that fully satisfies the requirements for the estimation of the standard error of Kappa is simple random sampling (SRS) (Stehman 1992), a simple random sample often neglects classes that are rare in a landscape. The use of a stratified sample ensures adequate representation of all classes, and Congalton (1988) has shown that stratified random sampling performs well where small areas need to be represented. A simple random sample of 300 points was generated and compared with a stratified random sample of 300 points. The stratified random sample provided more complete representation of the change classes than the simple random sample. The effects of using stratified sampling on estimation of Kappa has not been studied, however Stehman (1992) did find the effects of using systematic sampling on estimation of khat to be small. Based on these considerations, it was decided to use the stratified random sampling scheme in order to maximize representation of change classes in the sample.

The stratified sample was selected based on a rasterized version of the reference change classification. This ensured that most change classes were adequately represented in the sample. Sample site selection criteria required that each sample pixel be completely

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surrounded by pixels of the same class to avoid isolated pixels (i.e. a 3x3 majority window with a 9 pixel majority threshold).

Various papers have been written concerning the minimum sample size necessary for accuracy assessment (e.g. Ginevan 1979; Hay 1979; Rosenfield, Fitzpatrick-Lins, and Ling 1982), however often the statistical requirements for sample sizes are impractical, especially when dealing with a change error matrix which can comprise large numbers of classes. A sample size of 50 per class is recommended as a good general guideline for ensuring an adequate sample in each cell of a matrix by Congalton (1991), however this can still represent a prohibitively large sample when dealing with large matrices. Based on the relatively small area being assessed (8705 ha), and dangers associated with spatial autocorrelation, a sample size of 300 was chosen. This represented 150 samples per class for the change/no-change matrices, but only 20-25 samples per class in the 'from-to' classification.

A sample of 300 points was selected and both change/no-change and from-to change class reference values were assigned to each point. Points that fell in areas of water, on pixels obviously affected by haze or cloud shadows, or which bordered cover types, were eliminated, resulting in a final sample of 290 points. The number of points varied for each class, ranging from two for the rarest class to 105 for the forest class. The majority of classes were represented by ten or more points.

i) Performances of differencing algorithms in detecting individual change classes

The performances of the differencing algorithms in detecting different types of land-cover change were assessed through extracting the percentages of correctly classified points for each change class of the 290-point reference sample.

iii) Comparison of change-detection performance across differencing methods

The locations of change/no-change classes detected by the individual differencing algorithms were compared across methods to ascertain whether certain types of change were more consistently detected than others. This was achieved by generating an image file of pixel values equal to the number of methods that identified each pixel as change (Figure 4.4), and evaluating the result based on change classes of the reference classification.
Figure 4.4. Schematic showing procedure to compare corresponding classified pixels across methods
RESULTS

The different change detection methods all identified similar areas of change, but all differed in the extent and precise demarcation of the areas (Figures 4.5 to 4.15). The postclassification comparison analysis (Figure 4.5) identified generally larger and more contiguous areas of change than the differencing algorithms, as would be expected from data which had been vectorized and polygons less than 3 hectares eliminated.

Contingency tables and Kappa statistics

i) Change/no-change accuracies

Error matrices are listed in Appendix B. The 290-point reference sample represented ten change classes, of which scrub-to-pasture and scrub-to-forest were inadequately sampled with ≤ 5 points.

The overall percentage accuracy and Kappa coefficients of the change/no-change classifications showed the postclassification comparison technique to have performed better than the differencing algorithms (Table 4.5). Rank performances of the overall accuracy and Kappa analyses for the differencing algorithms were nearly consistent, with univariate mid-infrared bands 7 and 5 performing the best overall, and the NDVI and Tasseled Cap greenness axis performing the worst.

All error matrices were found to be highly significantly different from a random result at the 95% level. Pairwise comparisons of the change/no-change error matrices showed postclassification comparison to be significantly better than all the other methods, and the second Tasseled Cap transform to have performed significantly poorer than all other methods (Table 4.6). TM-band 2 and the mid-infrared bands performed significantly better than the NDVI; the first and third Tasseled Cap transforms and the first and second principal components did not yield significantly different results from each other.

User’s and producer’s accuracies for the change/no-change classes for all methods are summarized in Table 4.7. The producer’s accuracy reflects errors of omission, whereas the user’s accuracy reflects errors of commission (Story and Congalton 1986). The producer’s
Figure 4.5. Locations of change identified using postclassification comparison
Figure 4.6. Locations of change identified using band 2 differencing
Figure 4.7. Locations of change identified using band 3 differencing
Figure 4.8. Locations of change identified using band 5 differencing
Figure 4.9. Locations of change identified using band 7 differencing
Figure 4.10. Locations of change identified using NDVI differencing
Figure 4.11. Locations of change identified using Principal Component 1 differencing
Figure 4.12. Locations of change identified using Principal Component 2 differencing
Figure 4.13. Locations of change identified using Tasseled Cap brightness axis differencing
Figure 4.14. Locations of change identified using Tasseled Cap greenness differencing

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Figure 4.15. Locations of change identified using Tasseled Cap wetness axis differencing
Table 4.5. Overall accuracy and Kappa coefficients based on change/no-change classes

<table>
<thead>
<tr>
<th>Method</th>
<th>Overall accuracy based on sample of 290 points (a)</th>
<th>Kappa coefficient based on sample of 290 points (b)</th>
<th>Rank performance (c)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Postclassification comparison</td>
<td>0.85</td>
<td>0.60</td>
<td>1</td>
</tr>
<tr>
<td>TM band 2 differencing</td>
<td>0.80</td>
<td>0.38</td>
<td>4</td>
</tr>
<tr>
<td>TM band 3 differencing</td>
<td>0.78</td>
<td>0.30</td>
<td>9</td>
</tr>
<tr>
<td>TM band 5 differencing</td>
<td>0.80</td>
<td>0.39</td>
<td>3</td>
</tr>
<tr>
<td>TM band 7 differencing</td>
<td>0.81</td>
<td>0.41</td>
<td>2</td>
</tr>
<tr>
<td>NDVI differencing</td>
<td>0.76</td>
<td>0.36</td>
<td>10</td>
</tr>
<tr>
<td>PCA component 1 differencing</td>
<td>0.79</td>
<td>0.34</td>
<td>7</td>
</tr>
<tr>
<td>PCA component 2 differencing</td>
<td>0.80</td>
<td>0.38</td>
<td>5</td>
</tr>
<tr>
<td>Tasselled Cap transform 1 differencing</td>
<td>0.78</td>
<td>0.33</td>
<td>8</td>
</tr>
<tr>
<td>Tasselled Cap transform 2 differencing</td>
<td>0.69</td>
<td>0.11</td>
<td>11</td>
</tr>
<tr>
<td>Tasselled Cap transform 3 differencing</td>
<td>0.79</td>
<td>0.37</td>
<td>6</td>
</tr>
</tbody>
</table>

Rank performance (c) based on summation of rank performances of (a) and (b).
Table 4.6. Z-scores from pairwise comparisons of contingency matrices using kappa statistics

<table>
<thead>
<tr>
<th></th>
<th>TM band 2</th>
<th>TM band 3</th>
<th>TM band 5</th>
<th>TM band 7</th>
<th>NDVI</th>
<th>PCA1</th>
<th>PCA2</th>
<th>TCAP1</th>
<th>TCAP2</th>
<th>TCAP3</th>
</tr>
</thead>
<tbody>
<tr>
<td>TM band 3</td>
<td>1.431</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TM band 5</td>
<td>-0.281</td>
<td>-1.624</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TM band 7</td>
<td>-0.563</td>
<td>-1.878</td>
<td>-0.258</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NDVI</td>
<td>2.239</td>
<td>1.0567</td>
<td>2.369</td>
<td>2.715</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PCA1</td>
<td>0.643</td>
<td>-0.712</td>
<td>0.882</td>
<td>1.179</td>
<td>-1.581</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PCA2</td>
<td>-0.085</td>
<td>-1.454</td>
<td>0.191</td>
<td>0.460</td>
<td>-2.230</td>
<td>-0.702</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TCAP1</td>
<td>0.910</td>
<td>-0.440</td>
<td>1.135</td>
<td>1.444</td>
<td>-1.349</td>
<td>0.256</td>
<td>0.960</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TCAP3</td>
<td>0.047</td>
<td>-1.298</td>
<td>0.315</td>
<td>0.585</td>
<td>-2.081</td>
<td>-0.566</td>
<td>0.127</td>
<td>-0.820</td>
<td>-4.964</td>
<td></td>
</tr>
</tbody>
</table>

PCA1, principal component 1; PCA2, principal component 2; TCAP1, Tasselled Cap axis 1; TCAP2, Tasselled Cap axis 2; TCAP3, Tasselled Cap axis 3; PCC, postclassification comparison.

Negative values indicate superior performance comparing row on column; positive values indicate inferior performance comparing row on column; bold values indicate significance at the 95% level.
Table 4.7. User’s and producer’s accuracies for all methods for change/no-change classes

<table>
<thead>
<tr>
<th>Method</th>
<th>Change</th>
<th>No-change</th>
<th>User’s accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Change</td>
<td>No-change</td>
<td>Change</td>
</tr>
<tr>
<td>Postclassification comparison</td>
<td>0.66</td>
<td>0.92</td>
<td>0.74</td>
</tr>
<tr>
<td>TM band 2 differencing</td>
<td>0.35</td>
<td>0.96</td>
<td>0.75</td>
</tr>
<tr>
<td>TM band 3 differencing</td>
<td>0.29</td>
<td>0.96</td>
<td>0.71</td>
</tr>
<tr>
<td>TM band 5 differencing</td>
<td>0.41</td>
<td>0.93</td>
<td>0.69</td>
</tr>
<tr>
<td>TM band 7 differencing</td>
<td>0.39</td>
<td>0.95</td>
<td>0.75</td>
</tr>
<tr>
<td>NDVI differencing</td>
<td>0.30</td>
<td>0.92</td>
<td>0.56</td>
</tr>
<tr>
<td>PCA component 1 differencing</td>
<td>0.34</td>
<td>0.94</td>
<td>0.66</td>
</tr>
<tr>
<td>PCA component 2 differencing</td>
<td>0.38</td>
<td>0.94</td>
<td>0.71</td>
</tr>
<tr>
<td>Tasselled Cap transform 1 differencing</td>
<td>0.33</td>
<td>0.94</td>
<td>0.68</td>
</tr>
<tr>
<td>Tasselled Cap transform 2 differencing</td>
<td>0.25</td>
<td>0.84</td>
<td>0.36</td>
</tr>
<tr>
<td>Tasselled Cap transform 3 differencing</td>
<td>0.38</td>
<td>0.94</td>
<td>0.69</td>
</tr>
</tbody>
</table>

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accuracies for all methods were high for the no-change category, and low (except for postclassification comparison) for the change category, suggesting that changes were generally underestimated. The user's accuracies for the change and no-change classes did not show large differences between the two classes.

ii) Accuracy of postclassification comparison ‘from-to’ change classes

Analysis of the full change error matrix for postclassification comparison gives an overall accuracy of 76% and a Kappa coefficient of 0.68 (Table 4.8). Classes that were not well represented in the matrix (absent from the matrix, or column total ≤ 5) were rare (area ≤ 100 hectares (≈1230 pixels) in the reference classification) in the landscape (Table 4.3), and included classes with scrub as a ‘from’ or ‘to’ component, agriculture-to-forest, and forest-to-agriculture. These rare classes are indicative of the nature of changes occurring in the landscape, whereby most change that occurred between 1986 and 1996 represented conversion of pasture to agriculture, with some abandonment of pastures to forest, and some cutting of forests for pastures (see Chapter 3). The scrub category represents a transitory class between forest and non-forest areas, and is patchily distributed and difficult to classify (Chapter 3).

Areas of agriculture in 1986 were mostly misclassified as pasture, resulting in poor producer’s accuracies for the agriculture-to-agriculture and agriculture-to-pasture classes.

The spectral signatures of the pasture and agriculture are very similar in the 1986 image (Figure 4.16a). The crops that were present in 1986 comprised primarily citrus and African oil palm plantations (see Chapter 3): the oil palm would most likely have had pastures beneath the open palm canopy, thus resulting in spectral confusion of this crop with pasture. The pasture-to-agriculture class however, was better classified, probably because the areas of agriculture in 1996 represented primarily plantation agriculture of bananas and pineapples with spectral signatures distinct from the 1986 pastures (Figure 4.16b). The pasture and forest categories were well classified, although the pasture-to-forest category was
Table 4.8. Postclassification comparison full error matrix

<table>
<thead>
<tr>
<th>CLASSIFICATION</th>
<th>REFERENCE</th>
<th>No-change</th>
<th>Change</th>
<th>Row Total</th>
<th>Producer's Accuracy</th>
<th>User's Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>P-P</td>
<td>Ag-Ag</td>
<td>F-F</td>
<td>Sc-Sc</td>
<td>P-Ag</td>
<td>P-F</td>
</tr>
<tr>
<td></td>
<td>72</td>
<td>3</td>
<td>8</td>
<td>10</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Ag-Ag</td>
<td>2</td>
<td>3</td>
<td>24</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>F-F</td>
<td>2</td>
<td>3</td>
<td>102</td>
<td>9</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Sc-Sc</td>
<td>5</td>
<td>1</td>
<td>3</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>P-Ag</td>
<td>2</td>
<td>1</td>
<td>3</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>P-F</td>
<td>5</td>
<td>1</td>
<td>3</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>Ag-P</td>
<td>2</td>
<td>1</td>
<td>4</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>F-P</td>
<td>1</td>
<td>2</td>
<td>6</td>
<td>12</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Sc-P</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Sc-F</td>
<td>3</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Column</td>
<td>84</td>
<td>10</td>
<td>105</td>
<td>14</td>
<td>34</td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

P, pasture; Ag, agriculture; F, forest; Sc, scrub.

Producer's accuracy = diagonals/col total
User's accuracy = diagonals/row total
Overall accuracy (sum diagonals/total) = 0.76

Kappa Coefficient of Agreement = 0.68
Variance of kappa = 0.001
z statistic = 21.59
95% confidence interval for kappa: 0.672 < kappa < 0.679
Figure 4.16. Spectral signatures of land-cover types for 1986 and 1996

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overestimated, being confused with unchanged pasture. This is likely to be due to pastures with significant tree cover being confused as forest in the 1996 classification.

**Performances of differencing algorithms in detecting individual change classes**

The percentage accuracies of the differencing algorithms based on the change classes of the 290-point sample, and equivalent to producer's accuracy, demonstrated that the no-change categories for pasture, agriculture, forest, and scrub were all well identified as not having changed by all differencing algorithms (Table 4.9). The results showed varied performances however, in the identification of change classes across methods, which can be explained through examination of the spectral signatures, knowledge of changes that occurred in the area, and known sensitivities of the data transformations.

The pasture-to-agriculture class was the best-identified across methods, with the mid-infrared bands (5 and 7) and the Tasseled Cap wetness axis (also based on the mid-infrared bands) performing well. This was due primarily to the distinctive spectral signatures of the banana and pineapple plantations, which comprised the majority of to-changes for this category (Figure 4.17).

The only moderate success of the pasture-to-forest class across methods, and poor performance of the forest-to-pasture class, are harder to explain through examination of the mean spectral values. The variance in spectral characteristics of the pasture class, particularly in the near- and mid-infrared bands, resulting from different management strategies, height of grasses, species of grasses, percentage of tree cover, amount of woody debris, and age of the pastures, would have had an impact on detecting changes from and to this class. It is probable that incomplete clearance of woody understorey plants, and trees left to remain in areas that were converted from forest to pastures, contributed to the poor identification of change in the forest-to-pasture class. Similarly, errors in identification of change for the pasture-to-forest class was probably a result of semi-abandoned, unkempt pastures having a high percentage tree cover and other woody growth, which resulted in similar reflectances to those of young forest.
Table 4.9. Percentage accuracy of differencing algorithms by change class based on a 290-point sample

<table>
<thead>
<tr>
<th>Method</th>
<th>P-P</th>
<th>Ag-Ag</th>
<th>F-F</th>
<th>Sc-Sc</th>
<th>P-Ag</th>
<th>F-P</th>
<th>Ag-P</th>
<th>F-P</th>
<th>Sc-P</th>
<th>Sc-F</th>
</tr>
</thead>
<tbody>
<tr>
<td>TM band 2 differencing</td>
<td>93</td>
<td>90</td>
<td>98</td>
<td>100</td>
<td>50</td>
<td>33</td>
<td>15</td>
<td>36</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>TM band 3 differencing</td>
<td>90</td>
<td>90</td>
<td>100</td>
<td>100</td>
<td>53</td>
<td>22</td>
<td>8</td>
<td>7</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>TM band 5 differencing</td>
<td>88</td>
<td>80</td>
<td>98</td>
<td>100</td>
<td>65</td>
<td>22</td>
<td>23</td>
<td>21</td>
<td>50</td>
<td>0</td>
</tr>
<tr>
<td>TM band 7 differencing</td>
<td>90</td>
<td>80</td>
<td>100</td>
<td>100</td>
<td>56</td>
<td>44</td>
<td>31</td>
<td>21</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>NDVI differencing</td>
<td>81</td>
<td>90</td>
<td>100</td>
<td>93</td>
<td>41</td>
<td>22</td>
<td>15</td>
<td>38</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>PCA component 1 differencing</td>
<td>93</td>
<td>70</td>
<td>97</td>
<td>100</td>
<td>44</td>
<td>56</td>
<td>15</td>
<td>21</td>
<td>0</td>
<td>20</td>
</tr>
<tr>
<td>PCA component 2 differencing</td>
<td>90</td>
<td>80</td>
<td>98</td>
<td>100</td>
<td>52</td>
<td>22</td>
<td>23</td>
<td>14</td>
<td>50</td>
<td>0</td>
</tr>
<tr>
<td>Tasselled Cap transform 1 differencing</td>
<td>94</td>
<td>70</td>
<td>96</td>
<td>100</td>
<td>50</td>
<td>22</td>
<td>8</td>
<td>21</td>
<td>50</td>
<td>20</td>
</tr>
<tr>
<td>Tasselled Cap transform 2 differencing</td>
<td>71</td>
<td>60</td>
<td>97</td>
<td>86</td>
<td>32</td>
<td>22</td>
<td>15</td>
<td>21</td>
<td>0</td>
<td>20</td>
</tr>
<tr>
<td>Tasselled Cap transform 3 differencing</td>
<td>88</td>
<td>70</td>
<td>100</td>
<td>93</td>
<td>62</td>
<td>33</td>
<td>23</td>
<td>14</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Number of points in sample</td>
<td>84</td>
<td>10</td>
<td>105</td>
<td>14</td>
<td>34</td>
<td>9</td>
<td>13</td>
<td>14</td>
<td>2</td>
<td>5</td>
</tr>
</tbody>
</table>

P, pasture; Ag, agriculture; F, forest; Sc, scrub.
Figure 4.17. Spectral signatures of plantation crops based on 1996 TM-image
The poor performance of the agriculture-to-pasture class can be attributed to the very similar signatures of the 1986 agriculture class and the 1996 pasture class.

An examination of the percentage accuracies within methods revealed that the visible bands did not perform well in detecting change for the pasture-to-agriculture or the agriculture-to-pasture classes. The mid-infrared and Tasseled Cap wetness axis, however, did detect these changes, indicating that there were differences in the soil and canopy moisture contents between these two cover types. Band 2 (green) identified change for both pasture-to-forest and forest-to-pasture moderately well.

Comparison of change-detection performance across differencing methods

If all change methods performed consistently, the number of corresponding pixels classified as change by all ten change-detection algorithms would be expected to be high for areas of change, and low (or zero) for areas of no-change. Table 4.10 indicates that individual pixels of the no-change classes (P-P, Ag-Ag, and F-F) were relatively consistently classified across methods. The change classes, however, demonstrated variable results, with most being inconsistently classified across methods. The exception to this was the pasture-to-agriculture category, which was consistently identified across methods. Again, this may be a result of the distinctive spectral signatures of the plantation agriculture in the 1996 image promoting detection of change to this category.

DISCUSSION

To summarize, postclassification comparison performed significantly better overall than the image differencing algorithms. The mid-infrared bands 7 and 5, and the visible band 2 performed the best overall of the differencing algorithms, and were not significantly different from each other. The Tasseled Cap ‘greenness’ axis performed significantly worse than all other methods, and NDVI also performed poorly compared with the other methods.

Areas of no-change were generally well identified across methods, but overall, the differencing algorithms underestimated areas of change. Performances of change-detection across methods revealed problems in identifying changes associated with pasture due to variable pasture conditions in the study area; and differences in crop type between 1986 and

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Table 4.10. Number of methods identifying common pixels as change

<table>
<thead>
<tr>
<th>Number of methods</th>
<th>No-change classes</th>
<th>Change classes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>P-P</td>
<td>Ag-Ag</td>
</tr>
<tr>
<td>0</td>
<td>15543</td>
<td>970</td>
</tr>
<tr>
<td>1</td>
<td>3934</td>
<td>224</td>
</tr>
<tr>
<td>2</td>
<td>3015</td>
<td>267</td>
</tr>
<tr>
<td>3</td>
<td>2447</td>
<td>241</td>
</tr>
<tr>
<td>4</td>
<td>1987</td>
<td>297</td>
</tr>
<tr>
<td>5</td>
<td>1420</td>
<td>470</td>
</tr>
<tr>
<td>6</td>
<td>1002</td>
<td>367</td>
</tr>
<tr>
<td>7</td>
<td>704</td>
<td>303</td>
</tr>
<tr>
<td>8</td>
<td>439</td>
<td>265</td>
</tr>
<tr>
<td>9</td>
<td>214</td>
<td>186</td>
</tr>
<tr>
<td>10</td>
<td>65</td>
<td>49</td>
</tr>
</tbody>
</table>

P, pasture; Ag, agriculture; F, forest; Sc, scrub.
1996 led to confusion between pasture and agriculture. The most consistently identified change class across differencing methods was pasture-to-agriculture; the most similar algorithms based on performances of change-detection for specific classes were bands 5 and 7 and the Tasseled Cap wetness axis. The mid-infrared bands (7 and 5) performed well in terms of detecting changes from agriculture to pasture and vice-versa; and the visible band 2 performed moderately well in detecting changes between forest and pasture.

Underestimation of change with the differencing method could be attributed either to placement of the change/no-change thresholds too far from the mean, or indistinct spectral classes. If this was a result of poor placement of the change thresholds then one would expect the user's accuracies for the change class to be higher than they were (i.e. errors of commission for the change class to be low), given that the most spectrally distinctive change classes would be at the tail ends of the distributions and not affected by threshold placement. Spectral characteristics are more likely to be the cause of poorly defined change classes than poor placement of the change/no-change thresholds. The spectral curves for land-cover types (Figure 4.16) demonstrated that the class spectra were not always distinctive. They also showed how the spectra for the agriculture class changed over time as the crop types changed, thereby confusing the identification of change classes. Spectral variation within the same class and scene was also important (e.g. variation in pasture characteristics).

The poor performances of the vegetation-specific differencing algorithms (i.e. NDVI and Tasseled Cap greenness axis), which are sensitive to the near-infrared band, are probably explained by the fact that the majority of the study area was vegetated, resulting in little contrast in the near-infrared band across the scene for vegetation (Figure 4.18). More importantly, the pasture had a higher reflectance in the near-infrared band than the forest, presumably due to vigorous herbaceous growth in the pastures (see also Singh (1986) and Mas (1999)) which, when contrasted with band 3 (Figure 4.19), would certainly reduce the effectiveness of the NDVI and greenness axis of the Tasseled Cap transformation.

The superior performance of the postclassification comparison over the differencing method could be partly attributed to the use of all seven TM bands in deriving the classes, as
Figure 4.18. Near-infrared band, Landsat-TM
Figure 4.19. Visible band 3, Landsat-TM

1986 Landsat-TM band 3
Universal Transverse Mercator, zone 16, meters
opposed to extracting information from one or two bands only (the Tasseled Cap transforms
and the principal components analysis were the only other methods that used information from
all bands). Also, it had the advantage of avoiding direct comparisons of brightness values,
thereby avoiding problems associated with misregistration and external differences in the
images, which are difficult to completely remove. The 1996 image in particular had a high
percentage of clouds, cloud shadows and patchy haze which, despite efforts to avoid these
areas, may have affected the results of the differencing experiments. Such problems
associated with atmospheric conditions are specifically pertinent to lowland tropical zones
(see Mas 1999), and comprise an integral aspect of the process of satellite remote sensing of
tropical environments. Mas (1999), working in lowland Mexico with Landsat-MSS data,
attributed the superior performance of postclassification comparison over image differencing
and principal components analysis to external differences in the data, and also to intra-annual
differences in soil moisture and vegetation phenology.

A further advantage with postclassification comparison is that the individual
classifications take into consideration changes occurring within classes over time. This is
particularly important in areas where changes are dynamic, such as where the landscape
moves through different agricultural phases. These dynamically changing landscapes are
typical of the rural lowland tropics.

One clear disadvantage of postclassification comparison over other methods is that by
comparing classifications, the method is comparing broad, pre-defined categories, rather than
using the continuous range of image values provided by the data (Lambin 1997). This has
implications for increased errors as a result of spatial autocorrelation using this method.

The results of this study concur with those of Mas (1999), using Landsat-MSS data, in
detecting similar vegetation changes (forest-to-pasture, forest regeneration, and others), with
good overall performance of postclassification comparison and the poor performance of
differencing using NDVI (and the near-infrared band). Singh (1986) likewise found the MSS
near-infrared band to perform poorly in detecting forest clearing using differencing and ratioing
algorithms, which he attributed to vigorous vegetation growth in the cleared areas. He found
the visible MSS band 5 to perform best in distinguishing changes in forest cover, which concurs with the findings here for the visible TM band 2 in identifying changes between pasture and forest. Singh found classification methods, however, to perform worse than other change-detection techniques. This he attributed to poor individual classifications of each date. The mid-infrared bands available on the TM sensors are not available with MSS, thus the overall good performance of these bands could not be compared with results of other change-detection studies from tropical environments.

CONCLUSIONS

Spectral pattern-recognition land-cover change-detection is dependent on spectral characteristics of land-cover classes. Within class, within scene, and between scene spectral characteristics determine the spectral distinctness of change, and thus the ability to detect change. The change-detection methods compared in this study confirmed that different techniques do perform differently, both in terms of overall performances, and depending on the specific type of change.

The relatively good performance of the visible (band 2) and mid-infrared univariate band differencing algorithms for detecting different types of change, combined with the ease of which they are conducted and understood, make them an attractive option for change-detection. The problem of determining the optimal change threshold remains, and is dependent on the distribution of the data values and the spectral nature of the changes that occur. The postclassification comparison is more time-consuming and requires in-depth knowledge of the study area for all dates of the analysis.

The simplicity of univariate band differencing makes it ideal for rapid identification of change 'hot-spots'. The use of different bands selected for changes associated with specific cover-types would produce rapid results, and areas of interest could then be channeled into a more rigorous change-detection process, such as postclassification comparison. The new hyperspectral/high spatial resolution data will present researchers with huge amounts of data, much of which will be redundant. The use of Landsat-TM data with univariate band differencing to identify hot-spots of change would allow much smaller areas of approximately-
known change types to be analyzed. If the spectral responses of the change types are known
from their behavior with Landsat-TM data, then that knowledge would aid researchers in
selecting appropriate bands from hyperspectral data, thereby reducing the amount of data and
computer processing time required. In this way, large areas could be analyzed for change
while minimizing the time and resources needed to do so.

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INTRODUCTION

Some of the problems associated with spectral pattern recognition to characterize land-cover, and land-cover changes, have been discussed in the previous chapter, and include spectrally indistinct land-cover types and change classes, differences in external conditions between images, and the changing spectral nature of land-cover changes through time. An alternative to spectral pattern recognition with remotely sensed data is that of spatial pattern recognition, which uses the spatial arrangement of differences in pixel values (either brightness values or transformed values) relative to one another to characterize a scene.

Spatial pattern recognition techniques are employed frequently in landscape ecology using categorical data to characterize the arrangement of species, communities, and habitat patches within landscapes, and these techniques could potentially play an important role in terms of monitoring and identifying ecosystem changes (Li and Reynolds 1994). Research on the use of spatial patterns to characterize land-cover and land-cover changes using unclassified remote sensing data, however, has been more limited, although in the last decade the use of fractals in describing complexity in remotely sensed data has started to receive the attention of researchers. The potential of spatial statistics and metrics to describe patterns in remotely sensed data has implications for i) improving land-cover classifications (De Cola 1989; de Jong and Burrough 1995), and hence detection of land-cover changes, ii) providing rapid techniques for identification of hot-spots of change using remote sensing data (Lam et al. 1998), and iii) in this new era of large volumes of high resolution hyperspectral remote sensing data, providing rapid techniques to generalize image content to aid in scene and band selection (Lam et al. 1998).

The main purpose of this paper was to investigate the performance of fractal dimension as a technique to characterize unclassified remote sensing data, and to compare
the results with performances of other spatial pattern recognition techniques, including another spatial statistic—spatial autocorrelation, and non-spatial and spatial landscape metrics.

**SPATIAL STATISTICS**

**Fractals**

The concept of fractal dimension to measure shape or complexity of objects was first introduced by Mandelbrot in 1967 (Mandelbrot 1967). Fractal dimensions are based on fractal geometry, which differs from Euclidean geometry in that a line would have a Euclidean dimension of one, but would have a fractal dimension with a potential range of one to less than two, depending on the complexity of that line. Similarly, a surface has a Euclidean dimension of two, but would have a fractal dimension in the range of two to less than three depending on the complexity of the surface. The higher the spatial complexity of a line or surface, the higher its fractal dimension. Thus, fractal dimension can characterize the length, shape, or form of an object (Lam and De C 1993a). An important property of fractal geometry is that true fractals display self-similarity. In other words, the shape of a fractal object or surface is independent of the scale at which it is measured, thus measurements made at different scales are comparable. This property of fractals would potentially be very useful in terms of comparing remote sensing data of different scales from different sensors if a remotely sensed surface was truly fractal. In practice, most natural objects and surfaces are not pure fractals, and it has been suggested that studying changes in fractal dimensions across scales could provide insights into the scale of underlying processes using remotely sensed data (Krummei et al. 1987; Lam 1990).

A full explanation of fractals and their potential applications in geography can be found in Lam and Quattrochi (1992) and Lam and De C (1993a). Fractals have been used to characterize a variety of natural objects and surfaces, such as coastlines (Lam and Qiu 1992), ice-sheet surfaces (Rees 1992), topography (Klinkenberg and Goodchild 1992), land-cover classifications of remotely sensed data (De C 1989), and many others (see Lam and De C 1993a). Relatively little research into the use of fractals to measure remotely sensed data has been conducted, however, and most efforts have concentrated on the methods used...
to calculate fractal dimension (e.g. de Jong and Burrough 1995; Emerson, Lam, and Quattrochi 1999; Lam et al. 1998; Qiu et al. 1999).

Previous studies (e.g. De Cola 1989; Lam 1990; Qiu et al. 1999) have found values of D to vary for different land-use/land-cover types, and across spectral bands. Lam (1990) and Qiu et al. (1999) both reported urban cover-types to have higher dimensions than other (rural) types, despite using different remote sensing data types in different geographic areas. Others (e.g. De Cola 1989; Krummel et al. 1987) have related high fractal dimensions to the intensity of anthropogenic activity.

Whereas the computation of fractal dimensions for lines is derived directly from the theory of self-similarity, the three-dimensional nature of a remotely sensed scene requires a less intuitive algorithm. Three methods for calculating fractal dimension of surfaces have attracted most attention from researchers, and include the isarithm method, the triangular prism surface area method, and the variogram method. Available software for computation of each of these three methods is provided by the Image Characterization and Modeling System (ICAMS; Louisiana State University and National Aeronautics and Space Administration), one of the main purposes of which is the computation of fractal dimension (see Quattrochi et al. 1997 and ).

Lam, Qiu and Quattrochi (1997), using ICAMS, concluded that the variogram method for calculating fractal dimension was unsuitable for use with remote sensing imagery, which has a tendency to display higher dimensionality than topographic surfaces (Lam 1990), due to the method's tendency to instability with increasing surface complexity. Thus, this paper focuses on the isarithm and triangular prism surface area methods only.

The isarithm method has been described in detail by Lam and De Cola (1993b). This method derives from the walking-divider method of calculation of D for a line, whereby the number of line segments or steps required to 'walk' a line are counted. This is done for a series of step sizes based on a geometric progression (i.e. 1, 2, 4, 8 etc. units). A linear regression of the logarithm of number of steps multiplied by the step size (i.e. the length of the line) on the logarithm of step size is then computed, and the dimension of the line is calculated
as 1 minus the slope of the regression line. The number of points used to calculate the regression is equal to the number of step sizes calculated. The slope of the regression line is always negative because as the step size increases, the amount of detail in the line decreases, and the length of the line becomes shorter.

The walking-divider method is adapted to calculate the dimension of a surface by calculating the mean of the fractal dimensions of a series of isarithms (i.e. contours that follow a specific pixel value), with the final D value calculated as 2 minus the mean slope of the regression lines. The user must set the number of steps and the interval between isarithms. The number of rows and columns of the area being analyzed restrict the number of steps that can be calculated. In ICAMS only D values from individual isarithms whose $R^2$ values are ≥ 0.9 are included in the overall D calculation, and any isarithm for which a zero length is returned at any step size, is likewise rejected.

The triangular prism surface area method for calculating dimension for a surface was introduced by Clarke in 1986 and put forward as a computationally simple method (Clarke 1986). This method can be visualized by taking the values of pixels that make up the four corners of a square (the number of pixels on a side being equal to the step size), and extending lines vertically, of length equal to the pixel value, from each corner (Figure 5.1). The mean of the four corner values is calculated, and a vertical line equal to the mean value drawn in the center of the square. Lines are then drawn joining the top of each corner line to neighboring corners and the center line, generating facets of the top of an elevated prism. The area of the top of this prism is then calculated. This is repeated across the image, and the total surface area calculated. The procedure is repeated for each step size. The logarithm of surface area is then regressed against the logarithm of the area of the square (which is based on the step size), and the dimension calculated as 2 minus the slope of the line.

Conflicting results have been reported regarding the performances of the isarithm and triangular prism surface area methods. Lam, Qiu and Quattrochi (1997) found that the
Figure 5.1. Schematic showing triangular prism surface area method for calculation of fractal dimension
isarithm method performed well in returning D values close to those of true surface dimensions, whereas Klinkenberg and Goodchild (1992) found results with this method to be poor. Clarke (1986) criticized the isarithm method because the resulting dimension was likely to depend on the isarithm interval and on the actual isarithms used.

Consistently low dimensions using the triangular prism surface area method as first described by Clarke (1986) were reported by Jaggi (1993), de Jong and Burrough (1995), and Lam, Qiu and Quattrochi (1997). Subsequent to these findings Qiu et al. (1999) tested the performance of the triangular prism surface area method with a minor modification to the algorithm, which served to increase the resulting dimensions, and they found the results to be more accurate. The isarithm method was found to be less sensitive than the modified triangular prism surface area method to extreme pixel values, but in the absence of such noisy pixels the triangular prism surface area method was found to be very stable (Qiu et al. 1999).

Spatial autocorrelation

Spatial autocorrelation is a scale-dependent statistic that is used as an indicator of the degree of clustering, randomness, or fragmentation of a pattern. Moran's I index of spatial autocorrelation ranges from less than zero for objects/values that display negative autocorrelation (i.e. a high degree of dissimilarity), zero for random patterns, and greater than zero for positive autocorrelation (i.e. clustered patterns). There is an inverse relationship between fractal dimension and spatial autocorrelation, whereby a distribution with high spatial complexity/low degree of clustering would have a high D value and low Moran's I value (Cliff and Ord 1973). Little research has been conducted using spatial autocorrelation to characterize landscapes.

COMMON LANDSCAPE INDICES

The combination of fractal dimension with the use of other landscape indices to describe diversity (i.e. richness and evenness) and arrangement of patch types (i.e. the interspersion of different patch types, and dispersion of individual patch types) can be effective in characterizing landscape patterns (Olsen, Ramsey, and Winn 1993; Quattrochi et al. 1997).
Three commonly used indices to characterize landscape patterns include Shannon's diversity index, contagion, and fractal dimension from perimeter/area. Contagion is used as a measure of the degree of adjacency, or interspersion, of individual pixels; fractal dimension from perimeter/area is often used to measure shape complexity of patch types; and Shannon's Diversity Index is used as a measure of patch diversity which combines information about patch richness and spatial distribution.

**Shannon's Diversity Index**

Diversity indices are measures of landscape composition (i.e. relative proportions of the landscape in each patch type - evenness, and number of patch types - richness) as opposed to being measures of landscape configuration (i.e. the arrangement of patches in a landscape). Shannon's diversity index ($S$) is given by:

$$ S = -\sum_{i=1}^{m} P_i \ln(P_i), $$

where $m =$ number of patch types and $P_i =$ proportion of the landscape occupied by each patch type $i$ (McGarigal and Marks 1995). The index ranges from zero, and increases without limit. A landscape comprising only one patch will have a value of zero. As the number of patch types increases, or the proportional distribution of patch types becomes more even, or both, the index value increases. Shannon's diversity index has been found to be more sensitive to the number of patch types than evenness (McGarigal and Marks 1995).

**Contagion**

Contagion ($C$) has been used widely as a measure of the degree of clumping and fragmentation of patches in a landscape. Li and Reynolds (Li and Reynolds 1993) give the equation for $C$ as:

$$ C = 1 + \frac{\sum_{i=1}^{m} \sum_{j=1}^{m} P_{ij} \ln(P_{ij})}{2 \ln(m)}, $$

where $P_{ij} =$ probability that two adjacent pixels, randomly chosen, are of patch types $i$ and $j$. Contagion will equal 100% when all patch types are equally adjacent to all other patch types.
and approaches zero as the distribution of adjacencies becomes less even (McGarigal and Marks 1995). Contagion is sensitive to patch richness (Frohn 1998).

Fractal dimension from perimeter/area

Fractal dimension calculated from perimeter/area has been used widely in landscape ecology to describe patch shape complexity. This index, based on the log-log regression of patch area to patch perimeter, does not give a true determination of fractal dimension because it is derived from measurements taken at only one scale (Frohn 1998). This index ranges from one to two, with values close to one indicating a landscape made up of shapes with simple perimeters, and values close to two representing landscapes with very complex perimeters (McGarigal and Marks 1995).

PURPOSE OF THE RESEARCH

This paper compares the performances of selected spatial pattern recognition methods to characterize different land-cover types using unclassified Landsat-TM data for the study site in northeastern Costa Rica. The methods evaluated were i) fractal dimension using the isarithm method, ii) fractal dimension using the triangular prism surface area method, iii) spatial autocorrelation, iv) Shannon's diversity index, v) contagion, and vi) fractal dimension from perimeter/area. These statistics/metrics vary in their computational complexity, but are rapid to calculate, and all generate a single value.

METHODS

Data sources and preparation of subsets

Georeferenced Landsat-TM data of the study site from 1986, 1996, and 1997 were used for these analyses (Table 2.1). The 1986 and 1996 reference classifications described in Chapter 2 were used in selecting square or rectangular subset areas of approximately, and at least, 4096 pixels (333 hectares) each. The aim was to select ten approximately homogeneous areas of each cover-type (forest, agriculture, pasture, and scrub): five for the 1986 image, and five for the 1996 or 1997 images depending on the existence of cloud-cover.

1 A minimum size of $2^8 \times 2^8$ (=4096) pixels was required for calculation of fractal dimension using number of steps = 6.
In practice, fewer subset areas were selected because of the lack of homogeneous areas of cover-types of the specified size. Where possible, subsets were selected from the same locations for the 1986 and 1996/1997 data for comparison. Subsets for each area/date combination were generated from the original Landsat-TM data. In addition, the normalized difference vegetation index (NDVI) was calculated for each image, and NDVI subsets generated for each area/date combination.

Characterization of land-cover

Descriptive statistics for all seven Landsat-TM bands and NDVI were extracted for each subset.

Fractal dimensions using the isarithm and triangular prism surface area methods, and spatial autocorrelation, were calculated using ICAMS. The version of ICAMS used to calculate these indices was the updated version, which applies the correction for calculation of the triangular prism surface area algorithm (see Qi et al. 1999). The triangular prism surface area method of calculating fractal dimension requires that the values be normalized for comparison, thus the subset values were stretched over 0-255 using a minimum/maximum stretch prior to running the triangular prism surface area algorithm. Both the triangular prism surface area and the isarithm algorithms were run using six steps, which provided six points for computing the linear regression. The isarithm algorithm was run initially using an interval of ten, however the algorithm failed to return values for band 6 (thermal) and for selected subsets for the visible bands. The isarithm algorithm was re-run using an interval of two, which returned values for all non-thermal bands. The isarithm results for the thermal band (band 6) were excluded from further analysis and discussion, due to the instability of the isarithm method in calculating the dimensions for this band.

In addition to fractal dimension and spatial autocorrelation, contagion, fractal dimension from perimeter/area, and Shannon's diversity index were computed for each subset using the FRAGSTATS program (Oregon State University, Corvallis, OR). Also, patch richness (i.e. the number of distinct pixel values or 'classes') was calculated for each subset as a non-spatial measure of complexity. A wide array of landscape indices can be rapidly
calculated using the FRAGSTATS program (Oregon State University). Although this program was designed for use with classified data, it is possible to calculate the metrics using unclassified data, whereby a ‘patch type’ is represented by a distinct pixel value.

RESULTS AND DISCUSSION

A total of 24 subsets were generated, comprising ten forest, nine pasture, three agriculture, and two scrub areas (Figures 5.2 to 5.7). The forest subsets were the most homogeneous of the cover types because large extents of forest existed in both 1986 and 1996, and common areas for both dates could be selected. The pasture, agriculture and scrub classes were more fragmented; as a result, the subsets representing these cover types were not as homogeneous as the forest subsets, and common areas for both dates could not be isolated.

Subset statistics

The band statistics for each subset showed typical reflectance patterns for vegetation for the four cover types, with high near-infrared returns, and lower returns in the visible bands (Figure 5.8; Appendix C). Forest had the lowest, and scrub the highest, overall brightness values of the cover types. Variation, measured as standard deviations, revealed forest to have the least absolute variation of pixel values about the mean, and agriculture, pasture and scrub having progressively more variation about their means. This result could partially be explained by the differences in the degree of homogeneity of land-cover in the selected subsets, in turn being a result of differences in the spatial configuration of the four land-cover types. The mean coefficients of variation revealed low relative variation for the forest class for all bands in comparison with the other cover-types (Figure 5.9). The high coefficients of variation relative to the other bands for the near- and mid-infrared bands (bands 4, 5, and 7) indicate variation within each cover-type in plant biomass, and plant and soil moisture conditions. The low variation revealed for the thermal band (band 6) can be attributed to the lower spatial resolution of the band, the effects of resampling the 120 meter pixels to 28.5 meters, and the naturally small variation in temperature across the landscape (Lam 1990).
Figure 5.2. Forest subsets: 1996
Figure 5.3. Forest subsets: 1986
Figure 5.4. Pasture subsets: 1986
Figure 5.5. Pasture subsets: 1996/7
Figure 5.6. Scrub subsets: 1986
Figure 5.7. Agriculture subsets: 1986, 1996

Bands 4, 5, 3
Figure 5.8. Subset means and standard deviations by cover-type

Figure 5.9. Subset coefficients of variation by cover-type
The NDVI had high values for all cover-types, as was expected for vegetation. Forest showed the highest value, and scrub, pasture, and agriculture had progressively lower values. A direct inverse relationship between the coefficient of variation and NDVI values was revealed. Variation in NDVI would be expected to be lower than the variation in bands 3 and 4 due to the reduction of the effects of topography conferred by the NDVI transformation. This was found to be true for all cover types.

Fractal dimensions and spatial autocorrelation

The isarithm method revealed consistently higher dimensions (D) than the triangular prism surface area method for agriculture, pasture, and scrub (Figures 5.10 to 5.13). Values for forest however, showed mixed results, with the triangular prism surface area method yielding higher D values in the visible bands and in the mid-infrared band 7. This difference in the behavior of the isarithm method could be a result of the low degree of absolute variation (described by the standard deviation) of pixel values within the forest class for these bands. This would mean that any existing variation could potentially be undersampled depending on the isarithm interval and the specific isarithms used, thereby yielding no result or a low value. This argument is supported by the lack of results for band 6 for all cover types, which had a very smooth distribution, and the poor return of results when using an initial isarithm interval of ten, particularly of the visible bands for the forest class.

The results of the triangular prism surface area method showed distinct values of D across all six non-thermal bands for all cover-types (Figure 5.14). D values across cover types showed no relation to the coefficients of variation of spectral values for all bands, a finding that supports Lam's (Lam 1990) conclusion that both non-spatial and spatial statistics are necessary to fully characterize the variation in remote sensing data.

Forest had the highest overall D for all bands and NDVI, suggesting a greater spatial complexity, or lower clustering, of pixel values within the class. Scrub, pasture, and agriculture showed progressively lower D values across the six non-thermal bands. These results support findings of previous studies (De Cola 1989; Krummel et al. 1987) that showed decreasing values of D to be associated with cover-types representing increasing degrees of
Figure 5.10. Fractal dimensions and spatial autocorrelation: forest

Figure 5.11. Fractal dimensions and spatial autocorrelation: pasture
Figure 5.12. Fractal dimensions and spatial autocorrelation: agriculture

Figure 5.13. Fractal dimensions and spatial autocorrelation: scrub
Figure 5.14. Fractal dimension (triangular prism surface area method) by cover-type

Figure 5.15. Spatial autocorrelation (Moran's I) by cover-type
human influence. The large patches of relatively homogeneous banana plantations, for example, yielded lower D values for all bands and NDVI than the highly variable complex canopy structure of old-growth forests. Likewise, the scrub category, which is an intermediate category between forest and pasture, had a D value intermediate between the forest and pasture categories.

The standard error plots (Appendix D) showed forest to have the smallest standard errors across all bands, and no overlap with other cover-types. Agriculture, pasture, and scrub revealed overlapping standard errors, with agriculture consistently showing the greatest error across all bands. The large standard errors reflect the small sample size for agriculture (three subsets) and variation in D across the subsets. The subsets for agriculture, scrub and pasture were not as homogeneous as the forest subsets, and inclusion of some areas of the other two cover-types were unavoidable, thus the overlap in standard errors of the means of these cover-types would be expected. These results highlight the problem with ensuring an adequate number of points (steps) for calculating the regression, on the one hand, and analyzing areas that are too large to represent meaningful patterns in the landscape, on the other. However, the cover-types of scrub, pasture, and agriculture exist, by their nature, as smaller patches interspersed with each other, thus the subsets were valid representations of the complexity of these cover-types. In order to extract D values for more homogeneous areas of the more fragmented cover-types, finer resolution data would be required. The isolation of undisturbed forest from the other cover-types, however, does have potential in terms of using Landsat-TM data for distinguishing forest from non-forest cover over large areas, such as the Amazon. De Jong and Burrough (1995) proposed a local triangular prism surface area method, whereby a moving window calculated D values for each pixel and generated an image of D values. Such a procedure could be used in rapid change detection for large areas.

Moran's I index of spatial autocorrelation showed distinctive results for the forest class in relation to the other cover-types, with low positive values for the non-thermal bands (Figure 5.15). This suggests that the spatial distribution of pixel values for forest approached that of a
random distribution rather than a clustered distribution. The pasture, agriculture and scrub showed higher index values, suggesting more clustered distributions of pixel values. The standard errors (Appendix D) showed scrub and agriculture to have consistently higher errors across bands than the forest and pasture classes, and showed the mean value for forest to be distinct from the other cover-types.

Contrasting spatial autocorrelation (Moran's I index) with fractal dimension revealed the autocorrelation values to be inversely related to D values calculated with the triangular prism surface area method (Figures 5.10 to 5.13). The fractal dimension is expected to be low for clustered distributions and high for more fragmented distributions, thus an inverse relationship between spatial autocorrelation and fractal dimension was expected.

**Landscape indices**

Patch richness (i.e. the number of distinct pixel values or 'classes' in each subset) gives some indication of the variability of pixel values within each cover-type (Figure 5.16). Forest was found to have the lowest number of pixel classes for all bands, with agriculture, pasture, and scrub showing progressively more classes. These results are comparable to the standard deviations (i.e. absolute variation) of pixel values about the mean (see Figure 5.8).

Figure 5.17 shows an unclear general pattern of contagion with land-cover type. Generally, agriculture and forest showed relatively clumped distributions compared with the other cover-types, and pasture and scrub showed less clumped/more interspersed distributions of pixel values. Forest showed low values of contagion, however, for the vegetation-sensitive bands 4 and 5. Contagion values for NDVI showed no resemblance to the band responses. An approximate inverse relationship between contagion and patch richness was noted, presumably a consequence of the sensitivity of the contagion metric to patch richness.

Shannon's Diversity Index (S) demonstrated a clearer pattern than the contagion metric (Figure 5.18). Forest revealed low S values in relation to the other classes; scrub and pasture showed high values; and agriculture intermediate values. Exceptions were the band 4
Figure 5.16. Patch richness by cover type
Figure 5.17. Contagion by cover type
Figure 5.18. Shannon's diversity index by cover type
and NDVI values, which showed different relative values across cover-types. An approximately inverse relationship of S to contagion was revealed, as expected.

The sensitivity of contagion and Shannon's diversity index to patch richness was probably exaggerated in this study due to the high number of different patch types. As a result, these indices may not prove useful in characterizing unclassified remotely sensed data.

The Double Log Fractal Dimension (based on perimeter/area yielded no clear patterns across cover-types, but generally showed agriculture and pasture to have the lowest dimensions, and forest and scrub to have higher dimensions (Figure 5.19). The relative patterns between classes became less clear for the vegetation-sensitive bands 4 and 5.

The results of the landscape metrics would suggest that these metrics as indicators of spatial complexity in unclassified remote sensing data do not provide additional information to that provided by fractal dimension and standard band statistics. One explanation for this is that whereas with fractal dimension and spatial autocorrelation the actual values of the pixels, in addition to their spatial arrangement, are included in the determination of these statistics, the landscape metrics do not use the information provided by the value of each pixel, but simply recognize that they are different from one another. Thus, the landscape metrics use less information than the statistics, and a less informative result should be expected.

CONCLUSIONS

This study explored the potential of fractal dimension for characterizing complexity of Landsat-TM data for a lowland tropical environment. The results demonstrated that fractal dimension derived from the triangular prism surface area method was useful for characterizing spatial complexity, yielding results comparable with those of Moran's I index of spatial autocorrelation. The isarithm method of calculating fractal dimension was found to be sensitive to the degree of absolute spectral variation in a scene, and thus less robust than the triangular prism surface area method. Fractal dimension was found to vary by spectral band, and by different vegetation cover-types. Areas characterized by high degrees of human influence, such as large areas of plantation agriculture, displayed low fractal dimensions, whereas old-growth forest displayed high dimensions. Standard landscape metrics for
Figure 5.19. Double log fractal dimension by cover type
measuring complexity in unclassified Landsat-TM data were not found to be useful due to the high number of 'patch types' inherent in the data, and the reduction in information when pixel values are considered only as distinct patch types. The interpretation of fractal dimension in conjunction with standard image statistics (mean, standard deviation, coefficient of variation) has potential for characterizing land-cover types, and thus land-cover changes.

REFERENCES


CHAPTER 6
CONCLUSIONS

Land-cover and land-use change (LUCC) in a lowland tropical environment was the focus of this doctoral research project. The need for regional- and local-scale studies providing basic LUCC information for input to global models has become a priority in global change research. Detailed environmental information from remote sensing sources provides the means to study physical land-cover characteristics and changes. The availability of new hyperspectral and fine spatial resolution data has prompted questions regarding efficient, practical, and reliable methods to detect changes in land-cover using both old and new remote sensing data.

Multi-temporal remote sensing and geographic information systems were used to study the processes of land-cover changes for a site located in the lowlands of northeastern Costa Rica. The stated objectives of this study were to i) identify and map historical and current changes in land-cover and land-use in a lowland tropical site from 1960 to 1996, ii) identify the causal processes and driving forces of those land-use changes, iii) identify suitable methods to detect land-cover changes, through evaluating the performance of selected remote sensing image processing and GIS techniques using multitemporal Landsat Thematic Mapper (TM) data for the same site, and iv) identify suitable methods to extract spatial characteristics of land-cover, through evaluating fractal dimension, spatial autocorrelation, and standard landscape indices, using unclassified Landsat-TM data. Chapter 3 addressed points i and ii, chapter 4 addressed the evaluation of different image-processing methods (point iii), and chapter 5 addressed point iv.

A time-series of land-cover maps for the site was generated using Landsat-TM data and aerial photographs. The integration of these two data types permitted the creation of a dataset covering a period from 1960 to 1996, which would otherwise not have been possible. The differences in the spatial and spectral resolutions of the data resulted in a classification scheme that represented a compromise between the information contained in the two data types.
LAND-COVER AND LAND-USE CHANGES IN SARAPIQUI

The analyses of land-cover and land-cover changes in the region revealed a transition during the mid-1980s in the trajectory of land-cover changes, from development of extensive cattle ranches at the expense of forests, to more fragmented and intensive land-uses primarily derived from pastures. This transition was attributed to the closing of the settlement frontier. Throughout the entire period, however, three common forces driving change were identified: colonization processes, infrastructure development, and changes in export markets. These national-scale forces worked within the context of the local environment, including the historical context, to generate the present patterns of land-cover and land-use within the site. Three factors were identified at the local-level as potential predictors of sites of change: roads, local edaphic conditions, and distance to nearest location of recent change. A next step in this research would be to statistically model these factors to predict locations of change and test the model for past scenarios, and to do this for other lowland tropical environments which have similar land-cover histories (e.g. Central America and lowland Amazonia). Statistical modeling of local-level factors to predict future potential locations of change represents a first step in the modeling process. Results of local-level factors need to be incorporated with national-level socioeconomic forces to determine the types, and timing, of changes likely to occur.

The ability of the classified Landsat-TM data to detect changes in land-cover was restricted by the spatial scale of the data. The increased fragmentation and intensification of land-use that occurred after the mid-1980s in the study area represented changes that occurred at spatial scales finer than that of the classification. Prior to the mid-1980s the landscape was less fragmented, with larger contiguous areas of land-cover, thus the Landsat-TM data could adequately detect the dominant changes in the landscape. It becomes clear that, as lowland tropical sites become more fragmented, remote sensing data with finer resolutions than that provided by Landsat-TM are required.

The findings of these analyses concur with those of previous studies in other parts of the tropics on the relationship between roads and patterns of LUCC. Careful planning of road
construction may help mitigate against the effects of haphazard and widespread forest destruction. The importance of historical context in influencing future changes can likewise be used by managers and planners as a tool to help identify potential problem areas.

METHODS TESTING

The performances of the spectral pattern-recognition change-detection methods varied according to the degree of spectral distinctness of, and between, cover types. Postclassification comparison was found to perform better than the image differencing algorithms. However, the method requires a priori knowledge of the site, is time-consuming, and is more complicated than the differencing method. Of the image differencing algorithms, the mid-infrared bands and visible band 2 differencing gave the best results. The advantage of differencing is its simplicity and rapidity. Knowledge of basic band statistics, combined with knowledge of spectral signatures of the features of interest, would allow selection of the optimal band(s) for use in univariate image differencing. This method has potential for rapid detection of change 'hot spots'. The main disadvantages of image differencing are its sensitivity to external differences between the images being compared, and the need to select the change threshold.

These findings concur with those of other researchers working with Landsat-MSS data in tropical environments, that no single method can be identified as being superior to all others for detecting change for all types of environments. The selection of a change-detection method must depend on the required end-product of the study, the resources available, and the availability of information about the site.

Results of the spatial pattern-recognition methods to characterize land-cover using unclassified Landsat-TM revealed fractal dimension, calculated using the triangular prism surface area method, to clearly distinguish between the four different cover-types. The results were comparable to those of Moran's I index of spatial autocorrelation. An inverse relationship was recorded between fractal dimension and the degree of human influence associated with cover type. This ability of fractal dimension to characterize different land-cover types has real potential for detecting changes between different remote sensing images.
Additional research is required in this arena, as is the development of software designed to calculate local fractal dimension. This would permit calculation of 'dimension images', which could then be tested using, for instance, image differencing to detect change.

FUTURE

Increased availability of fine-resolution sensors will signal the start of true multi-scale remote sensing. Landsat-TM will provide a rich archive of data that will need to be integrated with the new fine-resolution data. Similar problems encountered in this study, integrating the aerial photograph data and Landsat-TM data, will arise as a result of differences in spatial and spectral resolutions. A potential future use of Landsat-TM is the identification of areas of interest (i.e. change), to be subsequently analyzed using fine-resolution data, as part of multi-scale remote sensing projects. Such 'hot spot' identifications could be carried out rapidly and simply using fractal dimension, univariate image differencing, or both.
### APPENDIX A

**EIGENSTRUCTURE OF NON-STANDARDIZED PRINCIPAL COMPONENTS OF THE COMMON EXTENT STUDY AREA**

#### a) 1986 TM data

<table>
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<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
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<td>-0.36</td>
<td>-0.81</td>
<td>0.19</td>
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</tbody>
</table>

**Eigenvalues**

|          | 4540.40  | 46.90  | 21.92  | 2.84  | 0.41  | 0.35  | 0.14  |

| %        | 98.43    | 1.02   | 0.48   | 0.06  | 0.01  | 0.01  | 0.00  |

#### b) 1996 TM data

<table>
<thead>
<tr>
<th>Band</th>
<th>Component</th>
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<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
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<td>-0.67</td>
<td>-0.54</td>
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</table>

**Eigenvalues**

|          | 4598.18  | 86.59  | 30.58  | 9.59  | 0.82  | 0.39  | 0.09  |

| %        | 97.29    | 1.83   | 0.65   | 0.20  | 0.02  | 0.01  | 0.00  |
### APPENDIX B
#### ERROR MATRICES

Table B.1. Error matrix for 1986-1986 TM band 2 differencing

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<thead>
<tr>
<th></th>
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<th>Producer's Accuracy</th>
<th>User's Accuracy</th>
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<td>Column Total</td>
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<td>214</td>
<td>290</td>
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<td></td>
</tr>
</tbody>
</table>

Producer's accuracy = diagonals/col total
User's accuracy = diagonals/row total
Overall accuracy (sum diagonals/total) = 0.80

Kappa Coefficient of Agreement = 0.38
Variance of kappa = 0.002
z statistic = 9.39
95% confidence interval for kappa: 0.372 < kappa < 0.382

Table B.2. Error matrix for 1996-1996 TM band 3 differencing

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<th>Row Total</th>
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<td>Column Total</td>
<td>76</td>
<td>214</td>
<td>290</td>
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<td></td>
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</tbody>
</table>

Producer's accuracy = diagonals/col total
User's accuracy = diagonals/row total
Overall accuracy (sum diagonals/total) = 0.78

Kappa Coefficient of Agreement = 0.30
Variance of kappa = 0.001
z statistic = 10.32
95% confidence interval for kappa: 0.302 < kappa < 0.309

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### Table B.3. Error matrix for 1996-1986 TM band 5 differencing

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<th>User's Accuracy</th>
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<tr>
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<td>0.69</td>
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<td>290</td>
<td></td>
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<tr>
<td>Total</td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>

Producer's accuracy = diagonals/col total  
User's accuracy = diagonals/row total  
Overall accuracy (sum diagonals/total) = 0.80

Kappa Coefficient of Agreement = 0.39  
Variance of kappa = 0.002  
z statistic = 8.62  
95% confidence interval for kappa: 0.389 < kappa < 0.400

### Table B.4. Error matrix for 1996-1986 TM band 7 differencing

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<td>30</td>
<td>10</td>
<td>40</td>
<td>0.39</td>
<td>0.75</td>
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<tr>
<td>No-change</td>
<td>46</td>
<td>204</td>
<td>250</td>
<td>0.95</td>
<td>0.82</td>
</tr>
<tr>
<td>Column</td>
<td>76</td>
<td>214</td>
<td>290</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Producer's accuracy = diagonals/col total  
User's accuracy = diagonals/row total  
Overall accuracy (sum diagonals/total) = 0.81

Kappa Coefficient of Agreement = 0.41  
Variance of kappa = 0.002  
z statistic = 9.34  
95% confidence interval for kappa: 0.406 < kappa < 0.416

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### Table B.5. Error matrix for 1996-1986 NDVI differencing

<table>
<thead>
<tr>
<th>CLASSIFICATION</th>
<th>REFERENCE</th>
<th>Change</th>
<th>No-change</th>
<th>Row Total</th>
<th>Producer's Accuracy</th>
<th>User's Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Change</td>
<td></td>
<td>23</td>
<td>18</td>
<td>41</td>
<td>0.30</td>
<td>0.56</td>
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<tr>
<td>No-change</td>
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<td>53</td>
<td>196</td>
<td>249</td>
<td>0.92</td>
<td>0.79</td>
</tr>
<tr>
<td>Column Total</td>
<td></td>
<td>76</td>
<td>214</td>
<td>290</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Producer’s accuracy = diagonals/col total
User’s accuracy = diagonals/row total
Overall accuracy (sum diagonals/total) = 0.76

Kappa Coefficient of Agreement = 0.26
Variance of kappa = 0.001
z statistic = 7.15
95% confidence interval for kappa: 0.252 < kappa < 0.261

### Table B.6. Error matrix for 1996-1986 principal component 1 differencing

<table>
<thead>
<tr>
<th>CLASSIFICATION</th>
<th>REFERENCE</th>
<th>Change</th>
<th>No-change</th>
<th>Row Total</th>
<th>Producer's Accuracy</th>
<th>User's Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Change</td>
<td></td>
<td>26</td>
<td>12</td>
<td>38</td>
<td>0.34</td>
<td>0.68</td>
</tr>
<tr>
<td>No-change</td>
<td></td>
<td>50</td>
<td>202</td>
<td>252</td>
<td>0.94</td>
<td>0.80</td>
</tr>
<tr>
<td>Column Total</td>
<td></td>
<td>76</td>
<td>214</td>
<td>290</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Producer’s accuracy = diagonals/col total
User’s accuracy = diagonals/row total
Overall accuracy (sum diagonals/total) = 0.79

Kappa Coefficient of Agreement = 0.34
Variance of kappa = 0.002
z statistic = 8.63
95% confidence interval for kappa: 0.336 < kappa < 0.345
Table B.7. Error matrix for 1996-1986 principal component 2 differencing

<table>
<thead>
<tr>
<th>REFERENCE</th>
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<th>Row Total</th>
<th>Producer’s Accuracy</th>
<th>User’s Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Change</td>
<td>29</td>
<td>12</td>
<td>41</td>
<td>0.38</td>
<td>0.71</td>
</tr>
<tr>
<td>No-change</td>
<td>47</td>
<td>202</td>
<td>249</td>
<td>0.94</td>
<td>0.81</td>
</tr>
<tr>
<td>Column</td>
<td>76</td>
<td>214</td>
<td>290</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Producer’s accuracy = diagonals/col total
User’s accuracy = diagonals/row total
Overall accuracy (sum diagonals/total) = 0.80

Kappa Coefficient of Agreement = 0.38
Variance of kappa = 0.002
z statistic = 8.80
95% confidence interval for kappa: 0.377 < kappa < 0.387

Table B.8. Error matrix for 1996-1986 Tasselled Cap brightness (axis 1) differencing

<table>
<thead>
<tr>
<th>REFERENCE</th>
<th>Change</th>
<th>No-change</th>
<th>Row Total</th>
<th>Producer’s Accuracy</th>
<th>User’s Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Change</td>
<td>25</td>
<td>12</td>
<td>37</td>
<td>0.33</td>
<td>0.68</td>
</tr>
<tr>
<td>No-change</td>
<td>51</td>
<td>202</td>
<td>253</td>
<td>0.94</td>
<td>0.80</td>
</tr>
<tr>
<td>Column</td>
<td>76</td>
<td>214</td>
<td>290</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Producer’s accuracy = diagonals/col total
User’s accuracy = diagonals/row total
Overall accuracy (sum diagonals/total) = 0.78

Kappa Coefficient of Agreement = 0.33
Variance of kappa = 0.001
z statistic = 8.64
95% confidence interval for kappa: 0.323 < kappa < 0.331
### Table B.9. Error matrix for 1986-1996 Tasselled Cap greenness (axis 2) differencing

<table>
<thead>
<tr>
<th></th>
<th>Change</th>
<th>No-change</th>
<th>Row Total</th>
<th>Producer's Accuracy</th>
<th>User's Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>REFERENCE</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Change</td>
<td>19</td>
<td>33</td>
<td>52</td>
<td>0.25</td>
<td>0.36</td>
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<tr>
<td>No-change</td>
<td>57</td>
<td>181</td>
<td>238</td>
<td>0.84</td>
<td>0.76</td>
</tr>
<tr>
<td><strong>Column Total</strong></td>
<td>76</td>
<td>214</td>
<td>290</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Producer’s accuracy = diagonals/col total
User’s accuracy = diagonals/row total
Overall accuracy (sum diagonals/total) = 0.69

Kappa Coefficient of Agreement = 0.11
Variance of kappa = 0.001
z statistic = 3.39
95% confidence interval for kappa: 0.103 < kappa < 0.110

### Table B.10. Error matrix for 1986-1996 Tasselled Cap wetness (axis 3) differencing

<table>
<thead>
<tr>
<th></th>
<th>Change</th>
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<th>Producer's Accuracy</th>
<th>User's Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>REFERENCE</strong></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Change</td>
<td>29</td>
<td>13</td>
<td>42</td>
<td>0.38</td>
<td>0.69</td>
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<tr>
<td>No-change</td>
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<td>200</td>
<td>247</td>
<td>0.94</td>
<td>0.81</td>
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<tr>
<td><strong>Column Total</strong></td>
<td>76</td>
<td>213</td>
<td>289</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Producer’s accuracy = diagonals/col total
User’s accuracy = diagonals/row total
Overall accuracy (sum diagonals/total) = 0.79

Kappa Coefficient of Agreement = 0.37
Variance of kappa = 0.002
z statistic = 8.55
95% confidence interval for kappa: 0.369 < kappa < 0.379
## APPENDIX C

### BAND STATISTICS BY COVER-TYPE

<table>
<thead>
<tr>
<th>Land-cover</th>
<th>Band</th>
<th>Mean pixel value</th>
<th>Standard deviation</th>
<th>Coefficient of variation (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Forest</strong></td>
<td>1</td>
<td>59.1597</td>
<td>1.6127</td>
<td>2.733326</td>
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<td></td>
<td>2</td>
<td>22.5074</td>
<td>1.3747</td>
<td>6.117606</td>
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<tr>
<td></td>
<td>3</td>
<td>17.2551</td>
<td>1.6404</td>
<td>9.541804</td>
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<tr>
<td></td>
<td>4</td>
<td>79.2138</td>
<td>13.2467</td>
<td>16.72602</td>
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<td></td>
<td>5</td>
<td>54.9247</td>
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<td></td>
<td>6</td>
<td>130.5577</td>
<td>0.6973</td>
<td>0.534237</td>
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<tr>
<td></td>
<td>7</td>
<td>14.1547</td>
<td>2.7503</td>
<td>19.5193</td>
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<tr>
<td></td>
<td>NDVI</td>
<td>231.4829</td>
<td>2.7503</td>
<td>3.420702</td>
</tr>
<tr>
<td><strong>Pasture</strong></td>
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<td>65.53633</td>
<td>3.841667</td>
<td>5.786768</td>
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<tr>
<td></td>
<td>2</td>
<td>27.64578</td>
<td>3.257556</td>
<td>11.73646</td>
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<tr>
<td></td>
<td>3</td>
<td>24.50967</td>
<td>5.350889</td>
<td>21.40013</td>
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<tr>
<td></td>
<td>4</td>
<td>88.48656</td>
<td>16.28611</td>
<td>18.24</td>
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<td>1.738222</td>
<td>1.296593</td>
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<td></td>
<td>7</td>
<td>22.799</td>
<td>6.710889</td>
<td>29.26238</td>
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<tr>
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<td>6.710889</td>
<td>8.963964</td>
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<tr>
<td><strong>Agriculture</strong></td>
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<td></td>
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<td>86.552</td>
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<td>6</td>
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<td>1.163333</td>
<td>0.891285</td>
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<tr>
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<td>17.58567</td>
<td>4.577333</td>
<td>27.21465</td>
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<td>NDVI</td>
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<td>4.577333</td>
<td>12.30294</td>
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<tr>
<td><strong>Scrub</strong></td>
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<td>5.07154</td>
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<td>27.12</td>
<td>3.246</td>
<td>11.8975</td>
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<td></td>
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<td>5.62</td>
<td>24.17302</td>
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<td>4</td>
<td>98.61</td>
<td>18.8485</td>
<td>19.50381</td>
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<tr>
<td></td>
<td>5</td>
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<td>14.695</td>
<td>20.20315</td>
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<tr>
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<td>2.385</td>
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<tr>
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<td>7</td>
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<td>6.409</td>
<td>30.90599</td>
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<tr>
<td></td>
<td>NDVI</td>
<td>229.9095</td>
<td>6.409</td>
<td>7.354519</td>
</tr>
</tbody>
</table>
Figure D.1. Mean ± 1-standard error for triangular prism surface area method by cover-type for band 1

Figure D.2. Mean ± 1-standard error for triangular prism surface area method by cover-type for band 2
Figure D.3. Mean ± 1-standard error for triangular prism surface area method by cover-type for band 3

Figure D.4. Mean ± 1-standard error for triangular prism surface area method by cover-type for band 4
Figure D.5. Mean ± 1-standard error for triangular prism surface area method by cover-type for band 5.

Figure D.6. Mean ± 1-standard error for triangular prism surface area method by cover-type for band 6.
Figure D.7. Mean ± 1-standard error for triangular prism surface area method by cover-type for band 7

Figure D.8. Mean ± 1-standard error for triangular prism surface area method by cover-type for NDVI
Figure D.9. Mean ± 1-standard error for Moran's I by cover-type for band 1

Figure D.10. Mean ± 1-standard error for Moran's I by cover-type for band 2
Figure D.11. Mean ± 1-standard error for Moran's I by cover-type for band 3

Figure D.12. Mean ± 1-standard error for Moran's I by cover-type for band 4
Figure D.13. Mean ± 1-standard error for Moran's I by cover-type for band 5

Figure D.14. Mean ± 1-standard error for Moran's I by cover-type for band 6
**Figure D.15.** Mean ± 1-standard error for Moran's I by cover-type for band 7

**Figure D.16.** Mean ± 1-standard error for Moran's I by cover-type for NDVI
# APPENDIX E
## LIST OF ABBREVIATIONS

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Full Form</th>
</tr>
</thead>
<tbody>
<tr>
<td>AVHRR</td>
<td>Advanced Very High Resolution Radiometer</td>
</tr>
<tr>
<td>BCNP</td>
<td>Braulio Carillo National Park</td>
</tr>
<tr>
<td>D</td>
<td>Dimension (fractal)</td>
</tr>
<tr>
<td>ESE</td>
<td>Earth Science Enterprise</td>
</tr>
<tr>
<td>FAO</td>
<td>Food and Agriculture Organization</td>
</tr>
<tr>
<td>GCP</td>
<td>Ground control point</td>
</tr>
<tr>
<td>GIS</td>
<td>Geographic Information Systems</td>
</tr>
<tr>
<td>GPS</td>
<td>The Global Positioning System</td>
</tr>
<tr>
<td>HDGC</td>
<td>Human Dimensions of Global Change</td>
</tr>
<tr>
<td>ICAMS</td>
<td>Image Characterization and Modeling System</td>
</tr>
<tr>
<td>ICSU</td>
<td>International Council of Scientific Unions</td>
</tr>
<tr>
<td>IDA</td>
<td>Instituto de Desarrollo Agrario</td>
</tr>
<tr>
<td>IGBP</td>
<td>International Geosphere-Biosphere Programme</td>
</tr>
<tr>
<td>IHDP</td>
<td>International Human Dimensions Program</td>
</tr>
<tr>
<td>IHP</td>
<td>International Hydrological Program</td>
</tr>
<tr>
<td>ISSC</td>
<td>International Social Science Council</td>
</tr>
<tr>
<td>LBA</td>
<td>The Large-Scale Biosphere-Atmosphere Experiment in Amazonia</td>
</tr>
<tr>
<td>LUCC</td>
<td>Land-use and land-cover change</td>
</tr>
<tr>
<td>MPCA</td>
<td>Multi-date Principal Components Analysis</td>
</tr>
<tr>
<td>MSS</td>
<td>Multispectral Scanner</td>
</tr>
<tr>
<td>NASA</td>
<td>National Aeronautics and Space Administration</td>
</tr>
<tr>
<td>NDVI</td>
<td>Normalized Difference Vegetation Index</td>
</tr>
<tr>
<td>NOAA</td>
<td>National Oceanic and Atmospheric Administration</td>
</tr>
<tr>
<td>NSF</td>
<td>National Science Foundation</td>
</tr>
<tr>
<td>OTS</td>
<td>Organization for Tropical Studies</td>
</tr>
<tr>
<td>SPOT</td>
<td>Systeme Pour l'Observation de la Terre</td>
</tr>
<tr>
<td>Acronym</td>
<td>Description</td>
</tr>
<tr>
<td>---------</td>
<td>-------------</td>
</tr>
<tr>
<td>SRS</td>
<td>Simple random sampling</td>
</tr>
<tr>
<td>TM</td>
<td>Thematic Mapper</td>
</tr>
<tr>
<td>UNESCO</td>
<td>United Nations Educational, Scientific and Cultural Organization</td>
</tr>
<tr>
<td>WCRP</td>
<td>World Climate Research Program</td>
</tr>
<tr>
<td>WGS</td>
<td>World Geodetic System</td>
</tr>
<tr>
<td>WMO</td>
<td>World Meteorological Organization</td>
</tr>
</tbody>
</table>
VITA

Jane M. Read was born in Somerset, England, in 1966. She received her bachelor's degree from the University of London (Queen Mary Westfield College) in 1987, graduating with first class honors in Environmental Science. After completing her master's degree in Surveying at the University of London (University College London), and working briefly as a surveyor in London, Jane moved to Bolivia, where she stayed for nearly four years. During that time in Bolivia Jane traveled extensively, working on nature conservation, ecotourism, and wildlife research projects. In 1994 Jane entered the doctoral program in Geography at Louisiana State University. Jane's interests include environmental/biogeographical applications of geographic information systems and remote sensing, with special emphasis on tropical environments; in particular, human-environment interactions and global change.
DOCTORAL EXAMINATION AND DISSERTATION REPORT

Candidate: Jane M. Read

Major Field: Geography

Title of Dissertation: LAND-COVER CHANGE DETECTION FOR THE TROPICS USING REMOTE SENSING AND GEOGRAPHIC INFORMATION SYSTEMS

Approved:

[Signatures]

Major Professor and Chairman

Dean of the Graduate School

EXAMINING COMMITTEE:

[Signatures]

Date of Examination: July 23, 1999