Land Cover and Land Use: Classification and Change Analysis

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Despite its international designation as a hotspot of biodiversity and tropical deforestation (Achard et al. 1988), the micro-scale land-cover mapping of southern Yucatán peninsular region remains surprisingly incomplete, hindering various kinds of research, including that proposed in the SYPR project. This chapter details the methodology for the thematic classification and change detection of land use and cover in the tropical sub-humid environment of the region. A hybrid approach using principal components and texture analyses of Landsat TM data enabled the distinction of land-cover classes at the local scale, including mature and secondary forest, savannas, and cropland/pasture.

Results indicate that texture analysis increases the statistical separability of cover class signatures, the magnitude of improvement varying among pairs of land-cover classes. At a local level, the availability of exhaustive training site data over recent history (10–13 years) in a repository of highly detailed land-use sketch maps allows the distinction of greater numbers of land-cover classes, including three successional stages of vegetation. At the regional scale, finely detailed land-cover classes are aggregated for greater ability to generalize in a terrain wherein vegetation exhibits marked regional and seasonal variation in intra-class spectral properties. Post-classification change detection identifies the quantities and spatial pattern of major land-cover changes in a ten-year period in the region. Change
analysis results indicate an average annual rate of deforestation of 0.4 per cent, with much regional variation and most change located at three sub-regional hotspots. Deforestation as well as successional regrowth is highest in a southern hotspot located in the newly colonized southern part of the region, an area where commercial chili production is large.

The objectives of this chapter are to describe and evaluate: (1) an experimental methodology that iteratively combines three suites of image-processing techniques (PCA, texture transformation, and NDVI); (2) the statistical separability of distinct land-cover signatures; and (3) a post-classification change detection for the region from 1987 to 1997 in order to derive regional deforestation rates, and identify the spatial pattern of deforestation and secondary forest succession. Specifically, a region encompassing 18,700 km² (those land units completely within the defined region; Fig. 7.1) was mapped using a maximum likelihood supervised classification of lower-order principal components of Landsat TM imagery after tasseled-cap and texture transformations.

1. Image Analysis for Tropical Forests

Image classification and change analysis are increasingly important in monitoring and modeling global land-cover and land-use change, particularly in tropical environments where such change is largely concentrated. An understanding of human or environmental causes of this change requires knowledge of extant landscape patterns and ecosystems, monitoring extents and rates of change in these systems, and an analysis of the driving forces and consequences of change. Tropical deforestation has been a focus of international concern, and lately, high resolution satellite data are employed in monitoring deforestation as well as successional regrowth (Baltaxe 1987; Berta, Mausel, and Harrington 1990; Campbell and Browder 1992; Gilruth, Hutchinson, and Barry 1990; Green and Sussman 1990; Kummer 1992; Malingreau, Tucker, and LaPorte 1989; Mausel et al. 1993; Nelson and Holben 1986; Sader, Stone, and Joyce 1990; Woodwell et al. 1987). Satellite imagery is considered to be the most reliable source of quantitative information about deforestation, shifting or swidden cultivation, and other land-cover and land-use changes in the American tropics (Sader et al. 1994). Although much work has focused on the use of NOAA (National Oceanic and Atmospheric Administration) AVHRR (Advanced Very High Resolution Radiometer), and NASA (National

Aeronautics and Space Agency) Landsat Thematic Mapper (TM) data, the number of land-cover types typically classified from such imagery has been small, with few notable exceptions (e.g., Defries et al. 2000). While offering relatively lower spatial resolution at 1.1 km, AVHRR data have proven to be rich data sources for the mapping of global land-cover at a high temporal resolution, particularly in drier eco-regions. Landsat TM, however, has been more effective at separating evergreen forest types in the humid tropics (DeFries and Townshend 1994; Hansen et al. 2000).

Until recently, remote sensing and GIS studies of forest-cover change focused on deforestation rates and patterns rather than those of successional regrowth. More recently, a better understanding of the extent and human and ecological dynamics of swidden cultivation (and its associated fallow successions) has emerged, as has the availability of higher temporal and spatial resolution imagery. This fortunate coincidence has refocused attention on using satellite imagery to monitor processes of successional regrowth and forest re-establishment, spurring efforts to map increasingly finer categories of tropical forest types, including various stages of secondary forest (Mausel et al. 1993; Sader 1995; Steininger 1996; Sohn, Moran, and Gurri 1999).

2. Review of Main Preclassification Image Processing Techniques Employed

Predefined classification schemes that assign each pixel of remotely sensed data to one among a set of discrete land-cover classes continue to be one prevailing tradition in image classification (DeFries et al. 1998, 2000; Loveland and Belward 1997). There are several disadvantages to such an approach, including: (1) the inability in post-classification change detection to identify within-class changes in land cover, such as progressive land degradation or continuously decreasing biomass levels, and (2) loss of information about within-class variation in vegetation characteristics (DeFries and Belward 2000; DeFries et al. 1995). Yet, when it comes to linking remote-sensing based land-cover classification with meso- and micro-spatial scale studies of the human dimensions of global change (Turner et al. 1995), it is crucial that land-cover classes relevant to land uses that prevail at those scales be discernible.

As is commonly accepted, most land-cover classification projects aim to explore methodologies that allow the distinction of the maximum achievable
detail in land-cover categories (Saatchi et al. 2000). This classification effort in the SYPR project had the same objective. Image classification in phase-one research was initiated on the following principle: in order to link remote-sensing assessments of land-cover change effectively to social science land-use models utilizing socio-economic data about the agents of change, it is essential to distinguish with as much precision as possible the appropriate thematic categories of interest (Geoghegan et al. 1998). Ongoing image-processing research in the project aims to address the shortcomings of the thematic classification approach to land-cover mapping through techniques such as subpixel vegetation characterization, including fuzzy membership functions (Eastman 1999; Settle and Drake 1993; Wang 1990). An initial delineation of land-use and land-cover classes, however, is highly valuable at the local and regional scales for land-cover monitoring as well as spatially based econometric and agent-based models of land-use change (Chs. 12 and 13).

In the southern Yucatán, aside from forest-based economies involving timber and non-timber forest products, the land uses that extensively dominate are swidden and some market agriculture for which a particular forest type is preferred (medium to tall forest on well-drained but relatively level soils). Pasture is also important in certain regions, although secondarily so. Associated with agricultural activities are various stages of forest succession, involving diverse fallowing strategies that, contingent on data availability on individual decision-making linked to the fallow parcel, may be spatially modeled. In addition, the distinction of various classes of mature forest is critical for ecological studies of species diversity and ecosystem structure and function. Such distinction of forest types is also relevant to the study of forest economies, since different forest types vary in their economic potential. For instance, seasonally flooded forests are typically not managed for timber production due to the high costs and logistical impossibilities that inventories and extraction activities would involve in such terrain. Forestry activities focus instead on medium-tall forests located on well-drained upland soils.

2.1. Principal Components Analysis

A wide variety of image-processing techniques have been investigated better to map the diverse land-cover classes prevalent in tropical forest ecosystems. Principal components analysis (PCA) is one common technique long used to (1) reduce data dimensionality, (2) allow image enhancement and improve signal-to-noise ratios by removing random and systematic noise from satellite image bands, (3) perform digital change detection, and (4) characterize seasonal changes in cover types (Byrne, Crapper, and Mayo 1980; Eastman and Fulk 1993; Gillespie 1980; Townshend 1984). The use of PCA as a noise reduction tool is well documented (Eastman 1999; Singh and Harrison 1985). In the absence of noise, pixels belonging to one land-cover class would demonstrate identical spectral signatures at different bands of the electromagnetic spectrum. In reality, the presence of class-dependent and class-independent noise results in the prevalence of variations in spectral signatures, even among pixels belonging to the same land-cover class (Sharma and Sarkar 1998). Class-dependent noise reflects natural variations in each land-cover class, while class-independent noise is caused by atmospheric scatter or absorption (random) and/or sensor calibration problems (systematic).

The principal components transformation is a multivariate statistical technique that produces uncorrelated linear combinations of the variables (pixel spectral response in electromagnetic bands), called principal components (Carr and Matanawi 1999; Gonzalez and Woods 1992; Jensen 1996). The technique produces each successive linear combination such that it has a smaller variance (smaller eigenvalues). Thus the first principal component is the linear transform that captures the most variation in the dataset, the second component captures a smaller variation not captured by the first component, and so on. The higher the linear intercorrelation among the original variables (bands), the larger the part of the total scene variance that is captured in the first few components (Singh and Harrison 1985).

PCA has been extensively used to reduce the number of variables in multispectral imagery, as higher-order components with smaller eigenvalues are assumed to contain relatively little information (ERDAS 1994; Lillesand and Kiefer 1994; Richards 1993). When used in discriminant or cluster analysis, higher-order principal components have been discarded to reduce the number of variables as well as required training data (Basili et al. 1994; Paradella et al. 1994). For instance, May (1986) used only the first two principal components of Landsat MSS imagery for discriminant mapping of vegetation classes. Other studies, however, caution that the use of PCA to reduce the number of variables for land-cover classification needs to be selective, owing to potential losses in the accuracy and power of land-cover discrimination as a result of discarding higher-order components that may contain important landscape information (Townshend 1984).
2.2. Texture Analysis

Textural transformations have been used to classify imagery for a variety of resource management applications, including sea ice determination using synthetic aperture radar (SAR) imagery, automated land-use mapping using black-and-white aerial photos, classification of urban land-use patterns, agricultural targets, and discrimination of vegetation types in humid tropical forests of the Amazon basin using JERSI-SAR data (Saatchi et al. 2000). Image texture means the spatial variation or distribution of (spectral) tones of pixels as a function of scale (Haralick 1979; Haralick, Shanmugam, and Dinstein 1973). Previous research in tropical forest environments has demonstrated the utility of texture information in the classification process, indicating that classification accuracy can be improved through the incorporation of spectral-spatial techniques in conjunction with maximum likelihood classification (Li et al. 1994). Spatial distributions of texture-tone have been modeled for use in image classification, with results indicating the utility of even lower-order texture measures in the process.

Local variance as a lower-order statistical measure of image texture can produce improvements in classification accuracy. For each band in an image, variance as a local texture measure is derived from the first-order histogram of a 3 × 3 window as follows (ERDAS 1994):

\[
\text{Variance}(S_M^2) = \sum_{i=0}^{k-1} (i - S_M)^2 P(i)
\]

where \( P(i) = N(i)/M \), \( N(i) \) is the number of pixels of the same grey level in the window,
M is the number of classes,
i is the pixel grey level, and
k is the maximum possible grey level.

Essentially, variance measures heterogeneity within the pixel window such that the more different the grey level values are from their mean, the greater the variance. The pixel window mean is a first-order texture measure, and can be computed as

\[
\text{Mean}(S_M) = \sum_{i=0}^{k-1} iP(i)
\]

Third- and fourth-order texture measures such as skewness and kurtosis respectively measure degrees of asymmetry of pixel value distributions around the mean, and the relative peakedness or flatness of the distribution.

Texture analysis for land-cover mapping is challenged in environments that contain land-cover classes with similar spectral scattering properties. In such environments, texture analysis can none the less yield promising results if undertaken with rigorous ground-truthing and exhaustive training site datasets, as well as imagery processed to capture major axes of spectral variation, such as obtainable from principal components analysis. As a contextual technique incorporating neighborhood information, texture analysis can result in a reduction of classification error rates (Jhun and Swain 1996; Sharma and Sarkar 1998; Swain, Vardeeman, and Tilton 1981; Welch and Salter 1971).

2.3. Normalized Difference of Vegetation Index

The Normalized Difference of Vegetation Index (NDVI) is a measure of relative biomass. It is calculated as

\[
\text{NDVI} = \frac{IR - R}{IR + R}
\]

where IR is the pixel value in the infrared band, and
R is its value in the visible red band.

NDVI may capture, depending on the season, variation among distinct vegetation types, and is useful in identifying vegetated land-cover patterns (Loveland et al. 2000). In fact, NDVI derived from the NOAA AVHRR platform is often considered the best dataset for land-cover classification outside the humid tropics, particularly in dry or strongly seasonal climates (DeFries and Townshend 1994; Stone et al. Townshend and Justice 1988; 1994; Tucker, Townshend, and Goff 1985). In general, vegetation indices are less useful in the humid tropics than in semi-arid regions. In regions where vegetation types display phenological differences that are strongly seasonal, however, vegetation indices may be useful tools in land-cover discrimination.

3.0. Land-Cover Types and Target Classification Scheme

This SYPR project study focuses on southwestern Quintana Roo and southeastern Campeche, Mexico (Fig. 1.1), a region dominated by
seasonal tropical forests (Chs. 2, 4–5): semi-evergreen, well-drained upland forests (*selva mediana* or *alta*) classified elsewhere as medium to tall stature (but noted as mid-stature in Ch. 4 with crown heights ranging 15–20m) semi-deciduous forest (Miranda and Hernández-X 1963). Also extensive are short-statured (5–10m), less deciduous, seasonally inundated (*selva baja*), and to a much lesser extent, seasonally inundated savannas dominated by flood-tolerant forb and grasses (Flores and Espejel 1994). Swidden or *milpa* cultivation is the predominant land use in the region (Fig. 6.1), along with pasture, forest management, and more recently, intensive chili cultivation and agroforestry. These uses generate the land covers evidenced in remotely sensed imagery capturing the region, along with secondary succession on abandoned or fallowed fields.

The target classification scheme was designed to be relevant to the socio-economic and ecological research components. From a land-use perspective, it was important to delineate swidden as well as pasture. Moreover, given the rise in jalapeño chili cultivation (Ch. 10), such cropping was an initial classification target. The preliminary ecological component of the project attempted to characterize the different natural vegetation types present in the area, notably upland and *bajo* forests. Research focused strongly on successional vegetation as well, significant to forest fallow swidden and the structure and function of secondary forests following this cultivation (Ch. 5). Informed by these needs and by local ecologists and social scientists familiar with the region, a target classification scheme was developed as detailed in Table 6.1.

4. Image-Processing Methodology

The overall image-processing methodology is detailed in Fig. 6.2. The image-processing steps involved geometric correction, noise removal using dehazing and principal components analysis, NDVI calculation, and texture analysis for neighborhood spatial context. The processed image was then used to develop training sites for target land-cover classes, which were then evaluated for separability and subsequently used in a maximum-likelihood supervised classification.

4.1. Preprocessing: Haze Removal and NDVI

Landsat TM images from several dates and three distinct WGS path/row sets (paths 19 and 20, row 47, and path 19, row 48) were used for this study. The individual images were first georeferenced to a UTM projection (UTM zones 15 and 16, Datum NAD27, Mexico) to under 0.5 pixel RMS error, then reprojected to geographic (latitude/longitude) coordinates. Following image registration, the TM scenes were dehazed using ERDAS Imagine’s sensor-specific Tasseled Cap transformation designed for Landsat 4 TM and Landsat 5 TM imagery (Kauth and Thomas 1976; Lavreau 1991). The
### Table 6.1. Target classification scheme

<table>
<thead>
<tr>
<th>Land-use/cover class</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>Very little surface water present in region</td>
</tr>
<tr>
<td>Savannah type 1</td>
<td>Locally designated 'talar'</td>
</tr>
<tr>
<td>Savannah type 2</td>
<td>Herbaceous wetland vegetation with green, leafy plants</td>
</tr>
<tr>
<td>Short stature, seasonally inundated forest (bosque forest)</td>
<td>Locally referred to as bosque or selva baja</td>
</tr>
<tr>
<td>Well-drained, medium-tall upland forest</td>
<td>Locally referred to as selva mediana or, on occasion, montaja</td>
</tr>
<tr>
<td>Cropland</td>
<td>Includes chico, which was not distinguishable from milpa fields in trial signature evaluations</td>
</tr>
<tr>
<td>Pasture</td>
<td>Mostly a few large private ranches, and some smaller-scale pastures, often ungrazed</td>
</tr>
<tr>
<td>Successional forests</td>
<td>The three structural classes correspond loosely to three stages of 1–3-year, 4–9-year, and 10–15-year successional stages. Environmental and anthropogenic factors, however, cause many regional exceptions to this structure-age relationship</td>
</tr>
<tr>
<td>Herbaceous</td>
<td></td>
</tr>
<tr>
<td>Shrub-dominated</td>
<td></td>
</tr>
<tr>
<td>Arboreal</td>
<td></td>
</tr>
<tr>
<td>Successional <em>Pteridium</em> (bracken fern)</td>
<td>Invasive species whose emergence and prevalence is strongly tied to land-use history and site characteristics</td>
</tr>
<tr>
<td>Clouds</td>
<td></td>
</tr>
<tr>
<td>Cloud shadows</td>
<td></td>
</tr>
</tbody>
</table>

**Fig. 6.2. Image-processing methodology.**

Transformation yields data components that are linear combinations of the TM bands, which correlate with brightness (albedo), greenness, wetness, and haze of the imagery. The brightness component captures, among other factors, principal variation in soil reflectance in a weighted sum of all bands. The greenness index is a contrast between the visible and near-infrared bands and correlates with amount of green vegetation in the scene. Wetness captures variation in soil and canopy moisture. For Landsat TM bands, an additional band correlated with haze is produced, and is removed from the image (ERDAS 1994).

As mentioned above, vegetation indices are used for semi-arid regions of the world rather than the humid tropics. In the study region, however, phenological characteristics (onset, peak, and seasonal duration of greenness) of vegetation associations combine with drainage patterns (seasonally flooded lowlands v. well-drained uplands) to produce a more diverse landscape than otherwise would be expected on a rolling, karstic topography with relatively little variation in soils, at least at the regional level (Martínez-Salas and Galindo-Leal n.d.). The prevalence of distinct vegetation types that vary in degrees of seasonality (deciduous character) and responses to anthropogenic use indicates that vegetation indices may be of benefit to classification. Therefore, an NDVI image was derived from the original red and infrared bands of the Landsat TM after radiometric correction for the removal of haze. NDVI images were produced for each image date for subsequent analysis, utilizing the red and infrared bands of each dehazed TM scene. The dehazed images were then processed using Principal Components Analysis to complete noise removal and reduce data redundancy.

**4.2. Principal Components Analysis (PCA)**

PCA was used here primarily for random and systematic noise removal and image enhancement for better visual interpretation, and secondarily to reduce data dimensionality. Random noise in an image scene is not uniformly distributed in multispectral space, but varies according to spectral bandwidth due to variable susceptibilities of band channels to atmospheric scattering. Thus, the bands of the visible spectrum display greater atmospheric scattering than do near- and mid-infrared channels.

Past studies argue that higher-order principal components may be discarded on account of their low variance, since the variance is a measure of information content and the information content remains unchanged under unitary transformation. However, other studies have shown that
higher-order components of Landsat TM bands can contain important information for land-cover classification (Lark 1995; Townshend 1984).

To eliminate differentially distributed noise in band space, and simultaneously capture maximum spectral information, PCA was performed on two separate band sets: visible and infrared. The visible range bands (blue, green, and red, or bands 1, 2, and 3) of the Landsat TM images were transformed to produce three orthogonal components, the first component of which captured most of the visible band variance in the dataset (Fig. 6.3a). The second and third principal components of the visible bands captured most scattering/absorption related random atmospheric noise in the scenes, as well as striping (Fig. 6.3b). These higher-order visible band components were discarded from future analysis. In a separate step, PCA was run on the three infrared bands (bands 4, 5, and 7) of Landsat TM to produce again three principal components, the first two of which captured the major part of the scene variance and were used for subsequent analysis. The third component was discarded.

Rather than an approach that derives principal components transformations of all spectral variation jointly considered in 7-band spectral space, this two-tiered approach partitioned the principal components into two groups, later selecting the lower-order components from each group as representative of the most noise-free spectral information. Only the first principal component was selected from the visible group versus the first- and second-order components from the infrared group, owing to the higher atmospheric scattering and random noise in the first group and the relatively higher signal-to-noise ratios in the latter group. In this manner, the first and second principal components of the three infrared bands were stacked with the first principal component of the three visible bands to produce a 3-band PCA image that was used for all further analysis (Fig. 6.4a).

4.3. Texture Analysis

Next, indices of image texture were derived from the 3-band PCA image. By calculating spectral variance in spatial neighborhoods of pixels, texture analysis produced three additional bands of information based on the PCA image (Fig. 6.4b). The local texture measure was calculated from the first-order histogram of a $3 \times 3$ window using the formula for variance detailed in section 2.2. The variance characterizes the spatial heterogeneity of spectral reflectance around the central pixel of the chosen window. A small $3 \times 3$ window was chosen since terrain types were to be mapped on a pixel-per-pixel basis rather than as groups of pixels. Also, the small window size served to minimize edge effects observed in trial results of texture analyses using larger window sizes. The three texture bands were stacked with the three PCA bands to produce a 6-band image.

The NDVI image produced earlier from the originally dehazed red and infrared bands as detailed in section 4.1 was added to the PCA and texture

![Fig. 6.3 a, b](image1)
![Fig. 6.4 a, b](image2)
bands. Thus, a final 7-band image was generated for signature development and classification (Fig. 6.2).

4.4. Training Sites and Ground Truth Data Collection

Ground truth data was derived from a variety of sources: GPS-assisted field visits, topographic maps, vegetation and land-use maps, and detailed sketch maps of land-use history. Field studies for ground truth data were carried out in July 1997, January 1998, and March 1999. Trips were undertaken to identify areas representative of each land cover in the target classification scheme, and in later visits, to identify regions and causes of high classification uncertainty. The selection of areas for class-specific ground-truthing was strongly guided by project experts in local vegetation. As a result, sites were identified for seven cover classes, including water, two types of savannas, pasture, milpa, and bajo and upland forests. In addition, a diversity of successional forest patches ranging in age from 1 to 15 years were ground-truthed, as were areas of invasive bracken fern. Existing topographic and vegetation maps provided additional information on features such as water bodies, natural savannas and large, seasonally inundated bajos.

The ground-truthing benefited greatly from sketch maps derived in the field detailing smallholder land use in parcels over a period of 10–20 years. Sketch-mapping is a highly useful methodology in tropical forest environments to link better remote-sensing approaches to local-scale land change (Campbell and Browder 1995). Such maps were produced by project researchers during guided tours of agricultural plots belonging to interviewed farmers, and linked by GPS to the imagery (Fig. 6.5; also Ch. 9). In GPS-assisted visits, sketch-mapping documented the spatial pattern and history of land uses (Geoghegan et al. 2001; Turner et al. 2001). While map quality varied with farmer memory and surveyor accuracy, a ranked qualification by project personnel engaged in the survey aided in identifying the best maps for training site development. With the added ground truth data from the sketch maps, it was possible to increase the numbers of training sites for milpa, pasture, and chili, categories later coalesced into one agricultural cover class. Sketch maps also aided in the identification of additional training sites for successional forest classes. Since the maps were collected over a longer time period (one year) over a wider geographic area, they complemented well the more directed but shorter field visits for training site identification.
4.5. Training Site Evaluation

Signature development involved the creation of training sites for land-cover classes of the target classification scheme. After the development of training sites, the corresponding land-cover signatures were evaluated using four accepted measures of separability: Euclidean distance, divergence, transformed divergence, and Jeffries-Matusita distance. The parameters of these measures provide the statistical separation for all pairs of land-cover classes in terms of their spectral response patterns. In general, the larger the magnitude of the separability index used, the greater the statistical distance between training sets, and the higher the probability of correct classification (Lillesand and Kiefer 1994). The indices were calculated using the transformations (Swain and Davis 1978):

For each formula,

\( i \) and \( j \) = two signature classes being compared

\( C_i \) = covariance matrix of signature \( i \)

\( |C_i| \) = determinant of \( C_i \)

\( \mu_i \) = mean vector of signature \( i \)

\( tr \) = trace function

\( T \) = transposition function

Jeffries-Matusita distance (ranges from 0 to 1,414)

\[
\alpha = \frac{1}{8} (\mu_i - \mu_j)^T \left( \frac{(C_i + C_j)}{2} \right)^{-1} (\mu_i - \mu_j) + \frac{1}{2} \ln \left( \frac{\left| \frac{(C_i + C_j)}{2} \right|}{\sqrt{|C_i| \times |C_j|}} \right)
\]

\( JM_{ij} = \sqrt{2(1 - e^{-\alpha})} \)

Divergence

\[
D = \frac{1}{2} tr \left( (C_i - C_j)(C_i^{-1} - C_j^{-1}) \right) + \frac{1}{2} tr \left( (C_i^{-1} - C_j^{-1})(\mu_i - \mu_j)(\mu_i - \mu_j)^T \right)
\]

and Transformed Divergence (ranges from 0 to 2,000)

\[
TD_{ij} = 2 \left( 1 - \exp \left( \frac{-D_{ij}}{8} \right) \right)
\]

4.6. Supervised Classification

The final signatures were then used in a maximum likelihood supervised classification to produce categorical land-use and land-cover maps for change detection and modeling. In the supervised classification approach, the spectral response vectors of each class are modeled to have multivariate normal distributions, and the parameters of the models are estimated from training samples (Sharma and Sarkar 1998). Several training samples are developed for each cover class in the target classification scheme. In the maximum likelihood technique, pixel assignments to cover classes are based on likelihood calculated at each pixel for its membership in each candidate cover class. In the absence of contextual information, a maximum likelihood classifier assigns each pixel to one among the set of candidate land-cover classes, depending solely on the spectral response of that particular pixel. In the approach developed in this study, however, pixel assignments were based not only on per-pixel noise-corrected spectral response, but also on its neighborhood characteristics as determined by the textural transformation, as well as the pixel NDVI. The Bayesian maximum likelihood classifier is (ERDAS 1994):

\[
D = \ln(a_c) - \left[ 0.5 \ln(|Cov_c|) \right] - \left[ 0.5 (X - M_c)^T (Cov_c^{-1})(X - M_c) \right]
\]

where

\( D \) = weighted distance or likelihood

\( c \) = land-cover class

\( X \) = measurement vector of candidate pixel

\( M_c \) = mean vector of the sample of land-cover class \( c \)

\( a_c \) = probability that any candidate pixel is a member of class \( c \) (in this study equal prior probabilities were assigned to each cover class)

\( Cov_c \) = covariance matrix of pixels in sample class \( c \)

\( |Cov_c| \) = determinant of \( Cov_c \)

\( Cov_c^{-1} \) = inverse of \( Cov_c \)

\( \ln \) = natural logarithm
$T = \text{transposition}$

The pixel assignment is made to the class $c$ for which $D$ is lowest.

5. Change Detection

Assessments of land change for monitoring and projecting purposes require spatial specifications of where land change takes place, and are a critical component for land and forest management. Satellite remote sensing is a strong tool in the monitoring of forest clearing and land conversion over large areas such as the SYPR (Cihlar 2000; Lambin 1999).

5.1. Image Mosaics

Regional land-cover maps were created for the region to derive estimates of the major land changes in the past 30 years. The maps were created using the Landsat TM classified scenes as well as digitized aerial photographs. The study region is covered by portions of three Landsat scenes identified by the Landsat Worldwide Reference System as path 20, row 47; path 19, row 47; and path 19, row 48. Regional maps were created using TM images dating from 1984, 1985, 1987, 1988, 1994, 1995, 1996, and 1997. The regional land-cover map for 1969 was derived using aerial photographs that covered 63 per cent of the region. Most TM scenes pertained to the dry season (January to April) representing a relatively stable phenological status of the vegetation for these acquisition dates.

Two mosaics of the region were created using the TM scenes: one for the mid-1980s using scenes from 1984, 1985, 1987, and 1988, and the other for the mid-1990s using scene dates 1994, 1995, 1996, and 1997. The combination of scenes from different dates provides a more complete regional picture with less cloud coverage and solves some seasonal problems in class separability, such as those emerging from the deciduous behavior of both wetland and upland forest. As detailed in Table 6.1, eleven cover classes were initially identified, of which ten were land/vegetation based: water, wetland (bajo) forest, upland (mediana) forest, savanna (seasonally inundated), tular (herbaceous wetland), three stages of upland successional growth (herbaceous, shrub-dominated, arboreal), cropland, pasture, and one significant invasive species (bracken fern). The annual variability in precipitation throughout the region and the temporal variation in the imagery used to create the regional mosaics for the two periods of assessment, however, impeded such detail for the region at large. The ten land-cover classes were reduced to six for the regional analysis: wetland forest, upland forest, intermediate and late successional growth (4–15 years), tular-savanna (‘natural’ inundated and seasonally inundated grasslands, respectively), agriculture (cropland–pasture–early successional regrowth), and bracken fern.

Land-cover change estimates for the region were derived using the regional mosaics from TM and the 1969 map created from aerial photographs. Change detection was done through spatial cross-classification. Estimations of land-cover changes from 1969 to 1997 correspond only to 63 per cent of the total area (that covered by the 1969 aerial photographs), for three land-cover classes: forest, secondary growth (herbaceous and shrubby), and agriculture. Land-cover changes from 1987 to 1997 were estimated for the six classes. Rates of deforestation were estimated not only regionally but also for three subregional hotspots of change, to allow for quantitative comparisons across the region. The change hotspots included the Laguna Silvitic area in the west of the study region, the long-established ejido lands of Nicolas Bravo and Nuevo Becar in the east, and the recently opened southern area.

6. Results and Discussion

6.1. Classification

For each Landsat TM scene, the image used for classification included the 3-band output of the PCA, their three corresponding texture bands, and the NDVI band calculated before the PCA. Table 6.1 details the thirteen classes in the target classification scheme, and Table 6.2 the mean relative spectral response values of each class in each of the seven bands used. There was considerable regional variation in spectral reflectance within each land-cover class, inspiring trial classifications with merged and unmerged signature files, to test the effects of ‘averaging’ spectral signatures from various training sites for each land-cover class on the classification process. It was found that the merging of cover-class signatures leads to unsatisfactory classification results by strongly overclassifying particular land-cover classes such as wetland or upland forest. As a result, the final classification
Table 6.2. Mean pixel values for target land-cover classes

<table>
<thead>
<tr>
<th>Land cover</th>
<th>PC1</th>
<th>PC2</th>
<th>PC3</th>
<th>Texture 1</th>
<th>Texture 2</th>
<th>Texture 3</th>
<th>NDVI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>36.77</td>
<td>5.77</td>
<td>4.52</td>
<td>2.61</td>
<td>1.94</td>
<td>3.23</td>
<td>36.79</td>
</tr>
<tr>
<td>Savanna</td>
<td>50.54</td>
<td>14.47</td>
<td>23.92</td>
<td>2.40</td>
<td>1.38</td>
<td>4.091</td>
<td>56.56</td>
</tr>
<tr>
<td>Bajo forest</td>
<td>47.85</td>
<td>40.10</td>
<td>58.81</td>
<td>2.53</td>
<td>1.51</td>
<td>2.91</td>
<td>102.70</td>
</tr>
<tr>
<td>Upland forest</td>
<td>46.40</td>
<td>48.05</td>
<td>61.88</td>
<td>2.58</td>
<td>2.89</td>
<td>3.81</td>
<td>107.80</td>
</tr>
<tr>
<td>Cropland</td>
<td>63.94</td>
<td>24.86</td>
<td>96.84</td>
<td>4.70</td>
<td>5.74</td>
<td>8.14</td>
<td>80.36</td>
</tr>
<tr>
<td>Pasture</td>
<td>62.52</td>
<td>33.79</td>
<td>103.02</td>
<td>4.25</td>
<td>4.71</td>
<td>8.77</td>
<td>89.36</td>
</tr>
<tr>
<td>Herbaceous secondary</td>
<td>57.25</td>
<td>43.06</td>
<td>87.55</td>
<td>3.45</td>
<td>4.54</td>
<td>5.51</td>
<td>100.28</td>
</tr>
<tr>
<td>Shrubby secondary</td>
<td>51.46</td>
<td>52.04</td>
<td>73.24</td>
<td>2.75</td>
<td>4.48</td>
<td>5.13</td>
<td>110.07</td>
</tr>
<tr>
<td>Arboreal secondary</td>
<td>48.80</td>
<td>59.77</td>
<td>72.96</td>
<td>2.53</td>
<td>3.77</td>
<td>4.03</td>
<td>115.67</td>
</tr>
<tr>
<td>Pteridium (bracken fern)</td>
<td>50.54</td>
<td>14.47</td>
<td>23.92</td>
<td>2.40</td>
<td>1.38</td>
<td>4.09</td>
<td>56.56</td>
</tr>
<tr>
<td>Clouds</td>
<td>38.62</td>
<td>40.72</td>
<td>81.91</td>
<td>3.70</td>
<td>1.91</td>
<td>4.58</td>
<td>83.29</td>
</tr>
<tr>
<td>Cloud shadows</td>
<td>37.16</td>
<td>23.86</td>
<td>22.56</td>
<td>2.52</td>
<td>1.62</td>
<td>3.17</td>
<td>90.74</td>
</tr>
</tbody>
</table>

was conducted with disaggregate signature files, akin to a family of signature replicates per land-cover class, to include fully the regional variation within each land-cover class in the target classification scheme. In the final result, ten signature families were employed with over ninety-eight individual signature (training site) files.

Figure 6.6a shows the complete spectral profiles of each target-over class in all the seven bands used for classification. Profiles are of the same order of magnitude in the PC and NDVI bands, but of a lower order in the texture bands. Figure 6.6b details separately the signature profiles in the principal components and NDVI bands, while Figs. 6.6c and 6.6d detail the characteristic texture or spatial variation of the signature profiles. Figure 6.6d specifically depicts, for each target cover class, the mean spatial variance of spectral reflectance in 3 × 3 pixel neighborhoods. For each class, the composite stacked bar graph depicts overall mean neighborhood variance in the three principal components bands. For example, average variance for water was 2.61 in texture band 1 (based on the first principal component of original visible TM bands), 1.94 in texture band 2 (first principal component of infrared TM bands), and 3.23 in texture band 3 (second principal component of infrared TM bands), for a total average variance of 7.78 over the three texture bands. Wetland forest has the lowest average variance overall, followed by the water and savanna classes. Most of this total variance for these three classes comes from the first and third texture bands, indicating that the signatures for these
classes exhibit relatively more spatial uniformity in the first principal component of the infrared bands.

Compared to water, savanna, and bajo forest, upland forest has higher total variance (9.28), to which all three texture bands contribute in equal degree (Fig. 6.6d; Table 6.2). Additionally, the per-texture band variance of upland forest is higher than that of bajo forest, most of the difference (1.51 in bajo v. 2.89 in mediana) originating in texture band 2, and in turn the first principal component of the infrared bands.

Some land-cover classes are distinct spectrally, and their signature profiles reflect their unique spectral properties (Fig. 6.6e). The invasive bracken fern (*Pteridium aquilinum* (L.) Kuhn.), largely prevalent in the
eastern part of the study region (Ch. 4), is one such cover class. The high
discriminability of bracken was confirmed for classification purposes and
signature development in subsequent field visits. Other target classes that
are spectrally quite distinct include water and naturally occurring, season-
ally inundated savannas. These two classes are spectrally different but show
similar textural properties.

Land-cover classes that have similar spectral signatures in the PC and
NDVI bands are difficult to separate (Fig. 6.6f). A case in point is the spec-
tral similarity among wetland and upland forest, as well as the three stages
of successional vegetation. The signature profiles of these primary and
secondary forest classes show areas of overlap in principal components
band space. Particularly, upland and wetland forests are similar enough
spectrally to cause some overlap in signature profiles. A closer look at the
texture properties of these cover classes, however, indicates that variance
appears to aid in the separation of the signature profiles, particularly in the
second and third texture bands (based on the two lower-order principal
components derived from the original infrared bands of the Landsat TM
image). The spectral response of these two forest types may be similar, but
the spatial pattern of their spectral variation differs. Bajo forest has the low-
est spatial variance of spectral response, indicating it is a spectrally uniform
class relative to other classes, such as upland forest (Fig. 6.6d). This may
partly reflect actual structural characteristics of this type of forest. Another
factor contributing to the low spatial variability of bajo forest signatures
may be the fact that such forests are located on flat areas free from topo-
graphic effects such as hill shadows. The spectral signatures of upland
forests, on the other hand, exhibit more spatial variation, accounted for
by the local ecological variability of this thematic class, as well as slight
topographic effects in regions of gently rolling hills of the study area. In pre-
liminary studies, topographic normalization was attempted using an avail-
able DEM (Digital Elevation Model). Due to low-slope relief and
inadequate resolution of the DEM, the normalization algorithms did not
achieve appreciable improvements. Another potential cause of confusion
between bajo and upland forest is the presence of deciduous sub-
formations, locally referred to as subcaducifolia, that may occur within
either type of forest. This vegetation does not represent a forest type that is
exclusive to the two main forest categories, and training sites were not sepa-
rate developed for it. In future analyses, however, attempts are being
made to discriminate spectrally this land-cover class within both the two
forest types.

Secondary forest succession, pasture, and milpa are land-cover class
pairs that present separability challenges. They represent either areas under
a mix of different plant covers varying over short distances, or regions of
changing vegetation, such as in a successional sequence, or both. The case
of secondary successional classes is particularly problematic from a classi-
fication perspective, since sharp spectral thresholds do not exist among
early, mid-, and late successional forest patches. Thus, early herbaceous
successional vegetation blends spectrally and often spatially into mid-stage
shrub-dominated succession. The exact spectral (or age) divide between
shrubby mid-stage successional forest and late-stage, tree-dominated sec-
ondary forest is similarly difficult to identify. Rather than any linear or
determinate process, succession is strongly influenced by factors such as
land-use history, soils, slope and aspect, gap dynamics, and stand age.
These challenges are made all the more pressing by the fact that increasing numbers of research efforts identify the need to differentiate successional vegetation classes (Li et al. 1994; Mausel et al. 1993; Moran et al. 1994). These pairs are significantly improved with the incorporation of texture analysis, as demonstrated in Fig. 6.7. Most improvement attained through texture is between the cover pairs of early successional and crop/pasture, and mid- or late successional forest with mature upland forest.

Spectral signature separability varied greatly, depending on cover-class pairs. Figure 6.7 highlights the significant marginal improvements in signature separability obtained as a result of incorporating the three texture bands in the classification process. This improvement varies for different pairs of land-cover classes, and according to the separability index used (formulae in section 4.5). The highest marginal improvement in signature separability as a result of texture analysis was noted in distinguishing wetland and upland forest (Fig. 6.7). All separability indices used (Jeffries-Matusita distance, divergence, and transformed divergence) register the improvement.

Pasture and milpa, however, have very similar profiles on spectral reflectance as well as spatial variance (Fig. 6.6f). As depicted in Fig. 6.6d, these two classes have the highest overall variance of all the land-cover classes, a fact reflected in ground-based observation. Plots of milpa and small-scale pastures, particularly ungrazed pastures, are typically smaller in size and characterized by significant variation within the same plot, as well as variation among plots. This variation at a given moment (scene date) in existing vegetation at the scale of the individual parcels is due to a combination of site-specific environmental factors as well as differing land-use histories and strategies employed by the land manager. The smaller relative size of the plots also means that neighborhood variance calculations would register higher values overall, due to the presence of more edge pixels in the 3 x 3 windows used.

Milpa and pasture also reflected marginally higher separability as a result of the texture analysis, perhaps reflecting the fact that the largest areal extents of pasture are found on larger ranches rather than small, scattered plots on individual, ejido parcels. This fact could be reflected in the texture statistics, with most pasture training sites containing lower numbers of edge pixels in local pixel neighborhoods compared to milpa sites. In trial classifications, however, several areas of known pasture were misclassified as milpa, and vice versa. The classes of pasture and milpa were not satisfactorily separable at this stage of the classification process, and were merged into one agricultural cover class.

Although texture analysis aided in feature discrimination for some classes in the target scheme, useful information about some vegetation classes may have been lost as a result of the exclusion of the higher-order principal component bands, particularly in the visible bands. Future classification will revisit the PCA in order to manage better the differing signal-to-noise ratios in the TM bands. Also, future analysis might aim to identify the potential for developing texture functions using Fourier models, followed by testing the applicability of calibrated functions to other scenes within the same seasonal bounds. For the humid tropics, scene availability makes this a difficult issue.

The maximum likelihood Bayesian classification used relies heavily on a normal distribution of data in each input band, and tends to overclassify signatures with relatively large values in the covariance matrix. For classes such as upland forest, this is problematic since this class tends to have a large dispersion of pixels in the training samples and therefore large values in the covariance matrix for its signature. Additionally, the Bayesian classification was conducted with no preferential assignment of pixels to specific cover types. In other words, the prior probabilities for each land-cover class were assigned equal values. Future research will focus on the use of differential prior probabilities for certain land-cover classes that have relatively well-understood relationships to established GIS layers such as soils and topography.


The combination of aerial photographs and TM imagery analysis provides a spatially explicit picture of regional land cover and its change in the region (Fig. 6.8; color Pls. 1, 2; Tables 6.3–5). In 1969, just after the completion of Highway 186 but before its full paving, an area of 11,042 km² of the forests in the photographed region (central SYPR) was intact (Table 6.3). By 1987, 6.2% (686 km²) of this forest was lost, mostly within the older ejidos on the western and eastern edges of the study region. Over the next decade (1987–97), another 2.8% (288 km²) of this central area was deforested. At the full regional scale, 6.1% (970 km²) of the forest fell in the same decade (1987–97), reflecting the increased agricultural activity in the southeastern section not captured in the area covered by the 1969 aerial photographs (color Pl. 2; Tables 6.5–6). When successional regrowth (an area of 510 km²) is included in the derivation of net deforestation rates, a 2.9% rate of deforestation results for the 10-year
Table 6.3. Land cover (km²) in 1969, 1987, and 1997

<table>
<thead>
<tr>
<th>Land-cover classes</th>
<th>1969a</th>
<th>1987b</th>
<th>1997b</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest (upland + bajo)</td>
<td>11,042</td>
<td>10,356</td>
<td>10,068</td>
</tr>
<tr>
<td>Secondary succession</td>
<td>111</td>
<td>634</td>
<td>845</td>
</tr>
<tr>
<td>Agriculture and pasture</td>
<td>228</td>
<td>391</td>
<td>468</td>
</tr>
</tbody>
</table>

*a Based on aerial photographs covering 63% of the study region or 11,318km².
b Based on TM Landsat imagery for same area as photographs.


Table 6.4. Land cover (km²) in the mid-1980s and mid-1990s

<table>
<thead>
<tr>
<th>Image mosaics</th>
<th>Bajo forest</th>
<th>Upland forest (7–15 years)</th>
<th>Secondary agriculture and pasture</th>
<th>Bracken fern</th>
<th>Semi-inundated savannas</th>
</tr>
</thead>
<tbody>
<tr>
<td>1984–8</td>
<td>3,268</td>
<td>12,502</td>
<td>784</td>
<td>524</td>
<td>39</td>
</tr>
<tr>
<td>1994–7</td>
<td>3,264</td>
<td>12,064</td>
<td>1,060</td>
<td>599</td>
<td>149</td>
</tr>
</tbody>
</table>


<table>
<thead>
<tr>
<th>Land-cover classes in 1984–8</th>
<th>Bajo forest</th>
<th>Upland forest (7–15 years)</th>
<th>Secondary agriculture and pasture</th>
<th>Bracken fern n</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest</td>
<td>3,268</td>
<td>(99.2%)</td>
<td>0.3</td>
<td>(0.8%)</td>
</tr>
<tr>
<td>Secondary (7–15 years)</td>
<td>0.3</td>
<td>11,591</td>
<td>(92.5%)</td>
<td>(34.6%)</td>
</tr>
<tr>
<td>Agriculture and pasture</td>
<td>4</td>
<td>324</td>
<td>(41.3%)</td>
<td></td>
</tr>
<tr>
<td>Bracken fern</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>forest</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td></td>
</tr>
</tbody>
</table>

Note: Cover transitions are in km² with % change in parentheses.


Land Cover and Land Use

Fig. 6.8. Image Mosaics (each black-white tone represents a different date for TM scenes).

Table 6.6. Forest transitions (deforestation and succession) for three change hotspots (km²)

<table>
<thead>
<tr>
<th>Forest transitions from mid-1980s to mid-1990s (km²)</th>
<th>Forest to forest</th>
<th>Non-forest to non-forest</th>
<th>Forest to non-forest</th>
<th>Non-forest to forest</th>
</tr>
</thead>
<tbody>
<tr>
<td>Southern area</td>
<td>2,547</td>
<td>139</td>
<td>462</td>
<td>261</td>
</tr>
<tr>
<td>East-northeast area</td>
<td>2,058</td>
<td>85</td>
<td>305</td>
<td>176</td>
</tr>
<tr>
<td>Western area</td>
<td>1,499</td>
<td>105</td>
<td>101</td>
<td>187</td>
</tr>
<tr>
<td>Total SYPR</td>
<td>15,064</td>
<td>664</td>
<td>1,125</td>
<td>992</td>
</tr>
</tbody>
</table>

There is considerable spatial variation in the average deforestation patterns described above. Significantly higher rates of deforestation are found in the southeastern ejidos, bordering the eastern edge of the Calakmul biosphere reserve. In this area of about 3,300km², a total of 15.8% of extant forest was removed between 1987 and 1997. Adjusting for secondary succession, the net decadal deforestation lowers to 11.1%, almost three times higher, nevertheless, than the deforestation rate for the total region.
Another hotspot of change in the region is a 2,684 km² area in the east and northeast, including the ejidos of Nuevo Becar and Nicolas Bravo. This region experienced a 12.9% rate of deforestation and 3.6% of forest regrowth over the decade examined. Finally a third area with high rates of change is located to the west around Laguna Silvituca, wherein an area of almost 1,900 km² underwent 6.31% deforestation and 6.5% reforestation from 1987 to 1997 (Table 6.6).

These figures are consistent with the 0.4 per cent annual rates of deforestation estimated by Sader and colleagues (1994) for the northern Petén, Guatemala, immediately south of our study region. While large government-funded projects played an important role in deforesting wetland forests before the mid-1980s (Ch. 3), subsequent human disturbance has focused almost solely on upland forests, as indicated by the areas transitioning to and from the non-wetland land-cover categories (Table 6.5). Over the last decade examined, the amount of cultivated lands taken from mature upland forests seems to have decreased, and the focus of cultivation shifted to successional growth. This shift is illustrated by the amount of land cleared in the 1987 imagery and the amount fallowed (regrowth) in the 1997 imagery, especially along the southern roadway (Pl. 2). This shift may suggest a reduction in the milpa fallow cycle (less land taken from mature forest; more taken from early successional growth), a direction apparently indicated by the fourfold increase in area invaded by bracken fern (Table 6.5) and local claims of more intensive chili-swidden cultivation (Ch. 10). The area under bracken expanded from 39 km² to 149 km² in the past decade, much of the expansion occurring in the northeastern subregion centered around Nicolas Bravo (Fig. 6.9). This fern, the subject of future study, appears more prevalent in those areas entering second- or third-generation crop-fallow cycles and/or plots excessively depleted of their nutrients before fallowing (Ch. 5).

7. Summary

Landsat Thematic Mapper imagery was used to classify land cover in the subhumid tropics of the southern Yucatán peninsular region. Thematic information rather than within-class quantitative change was the primary goal of this classification effort, in order to link effectively to land-use change modeling studies. Texture analysis adds statistical dimensionality to spectral bands, incorporating information about the spatial context in pixel neighborhoods. The results of texture analysis were incorporated into the classification process as additional bands in the multiple-band classification algorithm. The results highlight the utility of synergism in social research and remote sensing.

For phase one of the classification effort, these observations apply:

- Integrating parcel-level studies of land-use history with remote sensing improves the level of classification detail and the relevance of the target scheme to ecological and socio-economic modeling needs.
- PCA is effective at random and systematic noise removal and reducing data dimensionality, particularly in the two-tiered approach
employed. Some fine-scale variations in spectral reflectance of certain land-cover types, however, may have been lost as a result of discarding higher-order components that captured most striping-related noise.

- Statistical texture analysis improves signature separability between several pairs of land-cover classes, but results are limited to the datasets from which the texture measures are derived. Future analysis may develop texture functions using Fourier models.
- Topographic normalization may improve characterization of wetland and upland forests, but a finer-scale DEM is required.
- Subdeciduous vegetation in both wetland and upland forests causes confusion among these land-cover classes. This vegetation may be characterized by its structure, biomass, and moisture condition, and if correctly classified, could lead to better bajolmediana separation.
- Secondary successional classes are separable at the local level, but at the regional level aggregation yields better generalizability. Trial experiments with tasseled cap transformations indicate that better separation may be achieved through this means among the different successional stages.
- Subpixel classification and fuzzy membership functions will yield richer, probabilistic land-cover information in the next stage of classification experiments.
- Accuracy assessment is underway to evaluate classification error and focus the development of additional training sites for more advanced classification efforts.
- Preclassification change detection can be combined with the results of transition maps derived in this stage to yield information on within-class changes, such as selective logging, land degradation, or decreasing biomass over the past decade.
- Annual deforestation rates are 0.32 per cent for 1967–97 and 0.29 per cent from 1987–97, most deforestation occurring from upland forests. There is significant regional variation in deforestation rates, rates of change being highest in the newly settled southern frontier.
- Large areas have undergone secondary succession, and the focus of cultivated lands appears to be shifting to successional forests, indicating a shortening of fallow cycles.
- Invasive species such as bracken fern have significantly expanded in areal extent, with potentially dramatic ecological and land-use consequences.

REFERENCES


