Remote Sensing Using AVHRR

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Dynamic Stratification of the Landscape of Mexico: Analysis of Vegetation Patterns Observed with Multitemporal Remotely Sensed Images

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Abstract

Rapid deforestation in Mexico, when coupled with poor access to current and consistent ecological information across the country underscores the need for an ecological classification system that can be readily updated and new data become available. In this study, regional vegetation resources in Mexico were evaluated using remotely sensed information. Multitemporal Global Vegetation Index (GVI) data from Advanced Very High Resolution Radiometer images provided ecological information at regional scales by being interpreted as phenological patterns of vegetation productivity and seasonality. Principal component analysis on GVI monthly composites identified spatial and temporal vegetation patterns, reducing their variation to five phenologically meaningful components. Sixty land-cover and natural vegetation classes were then derived via unsupervised classification from the five principal components. Additional phenological information (e.g., onset and peak of greenness, periods of growth) was obtained for each class. These data, along with seasonality measures (e.g., summer vs. winter peak of greenness) were used as criteria for grouping similar vegetation and land-cover types into a classification for Mexico.

Introduction

The natural landscape of Mexico has changed drastically in the last 30 years. Deforestation has reached unprecedented levels, a situation that is not likely to change significantly during this decade. According to the Mexican National Forest Inventory, 6 million hectares of all types of forest land were converted to other uses between 1964 to 1984, representing a loss of 25% from the total forested areas reported in the first national inventory (Inventario Nacional Forestal 1964, 1991). The estimated annual deforestation rate was 0.71% between 1980 and 1990, and projections suggest a deforestation rate of 0.55% for the current decade

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(Inventario Nacional Forestal 1991). Additionally, non official estimates indicate that the trend in Mexico is one of the highest among tropical ecosystems, with a deforestation rate approaching 10% in tropical forested regions (Myers 1993). Due to the high rate of landscape conversion, better decision making is needed for improved land-use policy development and implementation.

Presently, efforts to slow the rate of deforestation by implementing new land-use regulations are limited by a lack of information, especially at the regional level. A recently erected environmental law (Ley Forestal 1990) mandates that land managers apply ecological principles to forested areas, watersheds and national parks, via management and conservation plans. The long and short-term effects of disturbance are being evaluated primarily on the basis of regional data.

Regional ecological information for Mexico is not always available to decision makers. The most recent cartographic products related with natural resources in Mexico were obtained through visual interpretation of Landsat images from the 1970s. Mexican cartographic resources are, in general, outdated, inaccurate, and sometimes nonexistent (Hough 1993), and digital sources of information are just now becoming available (INEG1 1991). Because of the lack of map products, remotely sensed satellite data seem to be the most current source of information. Only such data can support regional landscape analysis at this time (Townshend *et al.* 1991). Remotely sensed data also provide statistically valid estimates of ecological parameters over large areal extents (Botkin *et al.* 1984).

Multitemporal analysis of ecological attributes at the regional scale is essential in understanding the dynamics of natural landscapes. Analysis of spatial and temporal variations of landscape features, such as vegetation and climate, is necessary to understand modifications in landscape structure resulting from land-use change, deforestation, and perturbation effects in general. Since the effects of landscape modification are revealed at several temporal and spatial scales over ecological gradients, it also is necessary to develop a framework analysis that integrates temporal variations and spatial heterogeneity of ecological landscape features. A landscape ecological classification defines such a framework, and is enabled when recurrent temporal and spatial patterns are stratified into ecologically meaningful landscape units.

There are several sources of satellite data that allow an objective analysis of ecological variables at different scales, from ecosystems to landscapes (Wickland 1991). Among them, the Advanced Very High Resolution Radiometer (AVHRR) from the National Oceanic Atmospheric Administration (NOAA) has two desirable characteristics: it has a high temporal frequency and its products are available at several scales of observation. Because of the daily frequency of AVHRR observations, there is a high probability of obtaining at least one cloud-free image in every part of the world each week or two using a composting technique (Oaring *et al.* 1989). Image composting allows the comparison of images collected over a sequential period (e.g., 7, 14, or 30 days) where the maximum measurement (e.g., normalized difference vegetation index, NDVI) is retained to represent the conditions observed during that particular period (Holben 1986).

AVHRR images are available at three grid cell sizes: (1) Global Vegetation Index (GVI), with a cell size of 16 km at the equator (GVI is a NDVI composite); (2) Global Area Coverage (GAC), with 1.1 by 4.4 km at nadir; and (3) Local Area Coverage (LAC), with 1.1 by 1.1 km cell size at nadir (Kidwell 1990). Different cell sizes in AVHRR products allow analysis of temporal trends of ecological variables associated with these observations at different spatial scales (Malingreau and Belward 1992), though each of these scales might be too coarse for local analysis.

The primary characteristics of AVHRR and its relationships with ecological variables have been discussed elsewhere (Box *et al.* 1989; Cihlar *et al.* 1991; Goward and Dye 1987; Goward 1989; Goward *et al.* 1991; Hastings and Emery 1992; Holben 1986; Roller and Colwell 1986). The most important AVHRR-derived variable for ecological applications is the NDVI, which has been shown to be well suited for vegetation analysis.

Previous work has shown that multitemporal NDVI images are useful for analyzing spatial vegetation patterns from regional to continental scales (Goward *et al.* 1985, 1987; Justice *et al.* 1985; Townshend *et al.* 1987; Tateishi and Kajiwara 1991; Tucker *et al.* 1985), and for assessing vegetation dynamics (Nelson *et al.* 1987, Nelson 1986). In addition, when a stratification according to some ecological criterion is needed, vegetation dynamics can be described using AVHRR (Eidenshink and Hass 1992). Practically, the imaging frequency and compositing process makes it possible to describe regional vegetation on a seasonal (phenological) basis (Lloyd 1991).

Environmental applications of AVHRR include land-cover mapping vegetation dynamic studies, tropical forest monitoring, fire risk assessment, vegetation production and biophysical parameter estimation (Ehrlich *et al.* 1994). However, multitemporal analysis of vegetation activity using remotely sensed data has become one of the main applications of AVHRR images. Using NDVI-AVHRR images, land-cover classes can be separated in a multitemporal space according to phenological, seasonal, and latitudinal variations in vegetation (Ehrlich *et al.* 1994).

Principal component Analysis (PCA) and Time Series Analysis are used frequently to capture the seasonal variation in multitemporal datasets (Townshend *et al.* 1985; McGwire *et al.* 1992, Eastman and Fulk 1993, Reed *et al.* 1994). PCA can be used to reduce the dimensionality of the multitemporal dataset, i.e., reducing the number of variables ("dimensions") in the analysis. However, the real potential of PCA lies in its ability to identify the true number of linearly independent vectors in the original matrix (Davies 1986). These linear vectors are interpreted as series of new and uncorrelated "components," which are combinations of the original variables (monthly NDVI values).

Principal components are usually computed from eigenvectors of the covariance matrix between variables. This results in orthogonal representations of variation (using and orthogonal rotation method) since the covariance matrix is symmetric. Although other methods of rotation can be used (Richman 1986), orthogonal rotations capture the periodicity inherent in the data (Goodman 1979). The components define linear combinations of original variables where their respective eigenvectors are proportional to the fraction of the variance of the original dataset accounted for by each component. Usually, the first component accounts for the majority of the variability; subsequent components explain residual (but still significant) variance, capturing all of the details in their modes of variation.

Because the resulting components reflect a combination of monthly NDVI values, their meaning is more complex than the original variables. Although the resulting interpretation of principal components derived from multitemporal NDVI analysis remains a matter of judgment, these can be related to seasonal vegetation activity, and their modes of variation can be mapped. Further, the spatial representations (images) of each component represent a series of latent images or trends that would be nearly impossible to detect by direct examination of the data (Eastman and Fluke 1993).

In this context, PCA assumes a meaningful interpretation of the components obtained. Previous studies are consistent in giving (at least for the first component) interpretation to PCA results. Generally, the first component is a measure of the non-seasonal and locational variability of vegetation, while the other components obtained can be quantitatively related to the "green up" or "brown down" of vegetation (Ehrlich *et al.* 1994). A classification into land-cover classes, using the components obtained with PCA, integrate the phenological variations of vegetation, while classifications using the original bands do not necessarily do so. However, the amount of seasonal variability captured by PCA depends on the number of months represented in the multitemporal dataset, year of observation, variability in the vegetation activity, and noisiness of the scenes (e.g., subpixel cloud contamination, sensor anomalies, etc.). In short, PCA is highly scene dependent, and results should be analyzed in the proper context.

The objective of this paper is to show how the application of remotely sensed data (specifically GVI images) can be used for multitemporal landscape analysis in Mexico using PCA. The application of PCA in multitemporal analysis of vegetation activity results in valuable phenological information that can be represented in several ways, including land-cover classifications. Although a previous land-cover classification for Mexico was developed using AVHRR composites (December and May) from NOAA-11 (Evans *et al.* 1992), this study constitutes one of the first attempts to capture the seasonal component in a vegetation/land-cover classification for Mexico. A recent effort using GVI data and PCA for Mexico showed that the seasonal component of vegetation can be captured (Turcotte *et al.* 1993) though the modes of variation were not analyzed in the phenological context.

The identification of recurrent multitemporal and spatial patterns in GVI images (and other AVHRR products) should result in improved sources of vegetation information for an ecological classification. The application of this technique to this specific dataset does not attempt to obtain a definitive classification for the country, but rather to illustrate how phenological information can be interpreted in an ecological sense. Better multitemporal vegetation information (than GVI) will be available through AVHRR (i.e., the NOAA/NASA Pathfinder AVHRR Land dataset) and other platforms (i.e., EOS) in the future, but this and other contributions using PCA techniques should help "standardize" the methods of approach.

Methods

Sources of Information

A subset of GVI (NDVI) monthly averaged observations (January to December) was extracted for Mexico from the global dataset developed by the Construction Engineering Research Laboratory (CERL) Environmental Laboratory in Champaign, IL (CERL, undated). The CERL-Global dataset contained monthly composited data for 45 months from April 1985 to May 1989; these were averaged into 12 monthly values. Although these monthly composited data may, at times for some portions of the globe, be contaminated by continuous cloud cover or spurious sensor artifacts, our examinatios of the 4-year averaged data did not show this to be problematic for Mexico. The NDVI is calculated from channels 1 and 2 of daily GAC data; its values are scaled (minimum value of 0 and maximum of 65) to represent the data, from no vegetation productivity to maximum vegetation productivity, in 8-bits (Kidwell, 1990). The cell size in all GVI images contained in the CERL-Global dataset were arbitrarily resampled to 4 minutes 48 seconds (0.08 decimal degrees) per grid cell, though the source data were 8.64

minutes per grid cell) (Tateishi and Kajiwara 1991).

Data Analysis

The original GVI data were mapped by month to obtain a phenological characterization associated with the Mexican vegetation during 1985-89. With the analysis of these data, the following phenological metrics about vegetation could be mapped: (1) maximum photosynthetic level, (or maximum monthly GVI score) for each pixel; and (2) minimum photosynthetic level (or minimum monthly GVI score) for each pixel (see Lloyd 1991).

PCA was applied to the GVI dataset to determine the statistical dimensionality of seasonal variations in the landscape. PCA also can reduce the total variation in the original 12 (monthly) GVI bands on an annual basis and produce components that are highly related with vegetation productivity and seasonality. The scree test, which estimates variation accounted for each component, was used as an aid in choosing the number of components to retain in subsequent analyses. An orthogonal rotated solution was applied to calculate the respective principal component scores. Respective component values were calculated for each resulting principal component and used as a set of new ecological variables for an unsupervised classification. The principal component procedure was implemented using the PRINCE algorithm in ERDAS software (ERDAS 1990).

For pattern identification, an unsupervised classification approach was preferred because there was no preconceived number or types of classes that define the landscape units. Sixty preliminary "greenness" classes were derived from the five principal component values using an iterative self-organizing data-analysis technique (ISODATA), which is a spatial classificatory algorithm (ERDAS 1990). The ISODATA algorithm was selected because it gives better results than other methods (e.g., statistical clustering using parallelepiped or minimum-distance methods) while identifying clusters inherent in the data. The 60 classes represent a stratification of the spatial and spectral variation captured by the principal GVI components across Mexico.

Original GVI values for each class were plotted by month to visualize the temporal pattern obtained with PCA. Each class had a characteristic "phenological signature" that represented photosynthetic activity during a correspondent period of growth. These signatures can be used to obtain a phenological classification of vegetation activity, according to Lloyd (1991). Even when phenology in vegetation is associated in an agricultural context (planting, fruiting, and harvest), it also has been defined as the "study of the timing of recurring biological events, the causes of their timing (due to biotic and abiotic forces), and interrelationships among species." Seasonality also can be defined in terms of the "occurrence of certain obvious biotic and abiotic events or groups of events within a definite limited period of the astronomic year" (Lieth 1974).

There are several phenological (timing of onset and peak) and seasonal (summer-winter difference in vegetation activity) variables that can be observed directly using multitemporal NDVI signatures for each class. The onset of greenness is observed at the month when there is a significant departure of previous GVI values (generally indicating an acceleration of the photosynthetic activity); the peak of greenness is determined when the maximum GVI value is reached for that class. Senescence in vegetation also can be also observed when greenness declines, and the end of the growing season can be identified when declining GVI values reach levels similar to those observed at onset. The duration of the growing season (in months) was identified by comparing the occurrence of onset and senescence dates in the signatures.

Three categorical maps (onset, peak, and duration of growing season) were obtained by reclassifying the unsupervised classes according to this phenological information. A more complete phenological characterization was then obtained by masking the onset, peak, and duration maps with the original GVI values. Vegetation index values for the "onset month" give the photosynthetic activity level at the beginning of the growing season, while GVI values at "peak month" give the photosynthetic level at the peak of the growing season.

Each of these variables was combined into a raster data base that describes the vegetation phenology variation in Mexico. A correlation analysis among all phenological factors was performed on the raster data to explore redundancy in the phenological set. Pearson's correlation coefficients were obtained using ARC/INFO's correlation command (ESRI 1995). Correlation coefficients were squared to obtain an estimate of the proportion of variance that can be explained by each phenological factor as a function of each other.

The 60 unsupervised classes were interpreted and labeled using vegetation types and land-cover categories reported in the "Land Use and Vegetation" map prepared by the Instituto Nacional de Estadística Geografía e Informática (INEGI 1980). This map at the scale of 1:1 million, was derived from visual interpretation of photographic Landsat products dating from the late 1970s. Obviously, there are several difficulties with this approach in labeling unsupervised classes. One problem is caused by the difference in dates between the GVI data and the creation of the map. Another problem surfaced because the patches corresponding to particular vegetation types in the INEGI map did not always match with the distribution of any particular class or set of classes in the GVI-derived data. In this case, the classes were named according to the most similar vegetation and land-cover category.

Results and Discussion

Spatial and temporal trends in GVI

The 12 monthly-averaged GVI images captured the annual and spatial variation of vegetated features in the landscape of Mexico during the period 1985-89 (Fig. 1). In addition, a summarization of original monthly GVI data shows maximum and minimum photosynthetic activity (Figs. 2a & 2b), which aids in interpreting the patterns elucidated by the satellite images.

These maps show predictable patterns in the vegetation, according to GVI variations: (1) the desert ecosystems in Baja California and northeastern Mexico never show much photosynthetic activity; (2) the tropical regions in the Yucatan Peninsula are highly photosynthetic for much of the year; (3) the conifer forests running along the "Sierra Madre Occidental" (western side of the county), which are largely pine forests, have relatively high GVI scores throughout the year but especially in the summer months; (4) the agricultural regions of central Mexico reach peak greenness during the summer months; (5) the deciduous

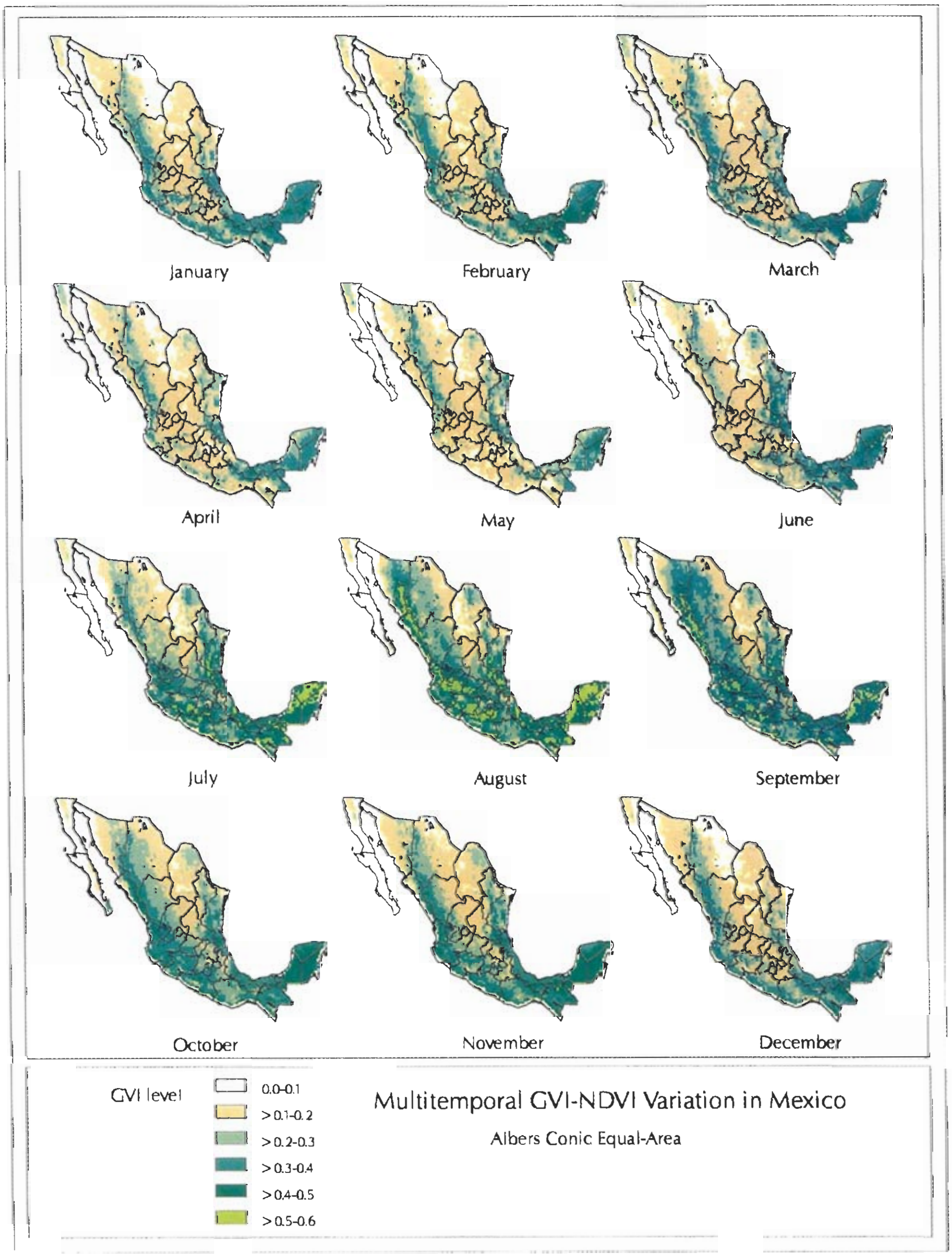

Figure 1 Multitemporal variation in vegetation activity. Monthly global vegetation index (GVI) from January to December.

vegetation in central Mexico also shows a phenological pattern similar to agriculture, and reaches maximum photosynthetic values during summer months; and (6) maximum photosynthetic activity is similar between tropical and temperate forests, though minimum photosynthetic activity is substantially higher in the tropical regions (Figs. 1, 2a & 2b).

Principal Components Analysis

A scree test in the PCA indicated that five principal components could be retained while explaining 94.7% of the variation in GVI. Thus PCA thereby reduced the dimensionality of 12 monthly GVI images into five phenologically meaningful components.

Scores for the five principal components were plotted by month to show the structure of each principal component (Fig. 3). This graph shows the PC structure in terms of the original variables (monthly GVI's) that are more associated with each principal component. PC1 is relatively constant across the year, whereas PC2 to PC5 have considerable seasonal variation. PC2 peaks in August and has its minimum in March, whereas PC3 peaks in December and has its minimum in May. PC4 and PC5 are bimodel in nature (Fig. 3).

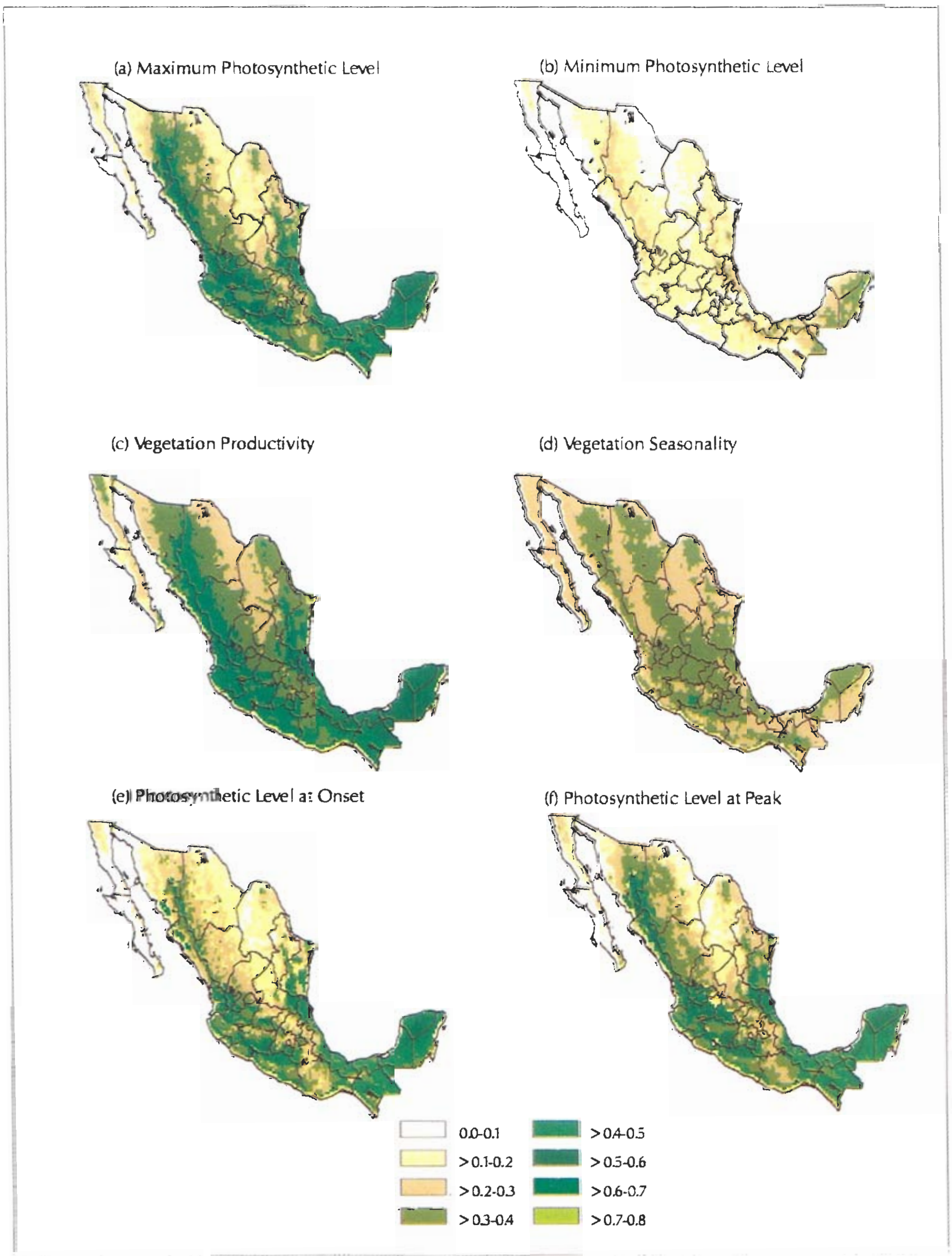

Figure 2 Phenological variation derived from 12 monthly GVI scores (scaled from 0 to1). (a) Maximum and (b) minimum photosynthetic activity, (c) vegetation productivity, (d) vegetation seasonality, (e) onset and (f) peak of photosynthetic activity.

The PCA also provided, with PC1 and PC2, the capability to map indirect measures of vegetation productivity and direct measures of vegetation seasonality (Figs. 2c & 2d). PC1 values showed an increasing trend in a north-south direction, highly associated with the neotropical-tropical pattern of vegetation distribution, i.e., very low values in the northern part of the country and the Penninsula of Baja California (where deserts and semideserts occur), and considerably higher values in the Yucatan Peninsula (where tropical vegetation occurs). As such, PC1 is highly related to vegetation productivity, as has been shown previously (Townshend *et al.* 1985; Goward and Dye 1987).

The pattern observed for PC2 showed that the country can be divided into two general areas according to vegetation seasonality. The first, or summer season growth zone (scores of > 0.3 in Fig. 2d), occurs in the lowlands of central and northern Mexico, as well as in the northern portion of the Yucatan Peninsula. In these areas, the associated vegetation is highly deciduous (deciduous selvas and agriculture). The second, or winter season growth zone (score < 0.3 in Fig. 2d), occurs in the extreme south, parts of the "Sierras," and in deserts of the northern portion of the country where perennial vegetation (deserts, conifers, and rain forests) dominates the landscape.

Classification of vegetation types

A classification based on five principal components rather than on the original 12 months of GVI data offers several advantages. First, the seasonal variation in vegetation identified through PCA can be included in the classification scheme. Vegetation types and land-cover classes can be described in productivity and seasonal components in addition to phenology. Additionally, subsequent multivariate analysis, which uses the components as a set of new ecological variables, can be performed for an ecological classification without temporal autocorrelation effects, and can be assumed to be statistically independent, i.e., multicollinearity effects on successive monthly observations are removed. Since each component obtained with PCA is not only orthogonal but also statistically independent, the classification will not be temporally autocorrelated and the differences among classes will be maximized with respect to the new phenological information.

The unsupervised classification on the principal components resulted in a definition of 60 land units (classes) associated with different seasonal vegetation patterns. In addition, since ISODATA is an algorithm that takes into account the spatial context, i.e., classifying neighboring pixels, the definition of classes primarily relies on the maximization of the variance between classes that are in close proximity, and minimizes the variation within the classes. Thus, the land units identified using the components classified with this algorithm are temporally and spatially homogeneous.

To rank the vegetation types as they are separated by each of the first three principal components, the PCA coefficients scores and class means of each of the 60 classes identified with ISODATA were plotted in the feature space plot created by PCA (Fig. 4). PC1 apparently corresponds well with the annual accumulated NDVI (Townshend *et al.* 1985), which differentiates the greenest features of the landscape from less green features (for Mexico, it clearly

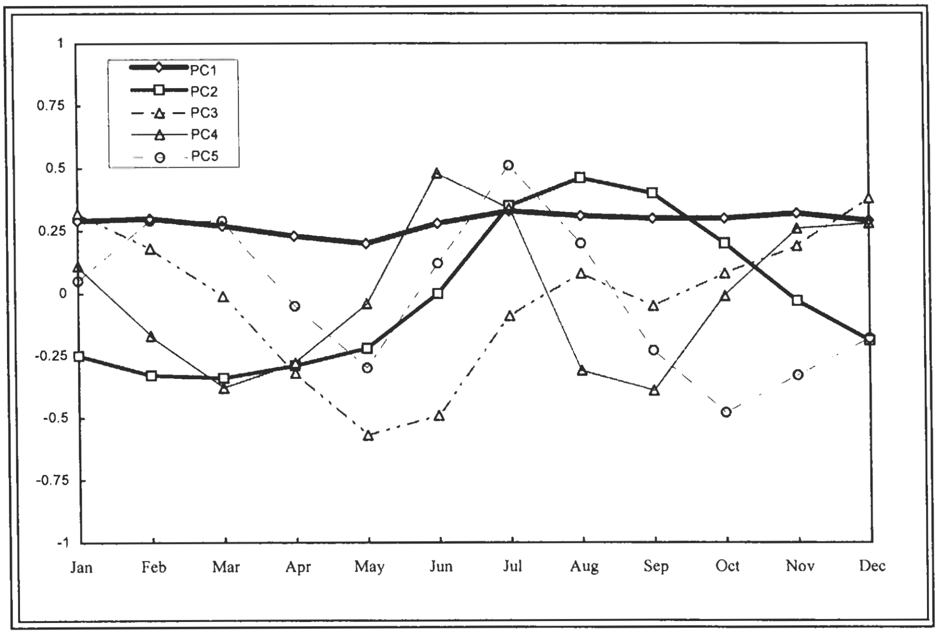

Figure 3 Principal component structure according to the variation in monthly factor scores coefficients.

differentiates selvas from deserts, Figs. 2a & 4). PC1 has been previously associated with annual integrated NDVI values in North America, which, in turn, are associated indirectly with functional ecological variables such as gross and net primary productivity, and actual evapotranspiration rates (Goward and Dye 1987).

PC2 is the primary component which captures the temporal variation of natural vegetation (Figs. 2d & 4). High PC2 values represent highly seasonal vegetation types that reach peaks of greenness during from July to September (e.g., low deciduous selva and rainfed agriculture). Lower values are mostly associated with seasonal vegetation that reaches peak of greenness from November to April i.e., coniferous forests. Thus, the maximum amplitude in PC2 variation is accounted for by summer-winter differences in vegetation growth (Fig. 4a).

PC3 to PC5 are seasonal components that differentiate features that are not associated with the "natural" seasonal variation identified by PC2. PC3 identifies areas that are associated primarily with agricultural zones irrigated during the winter season (Fig. 4b). PC4 and 5, though not shown graphically,

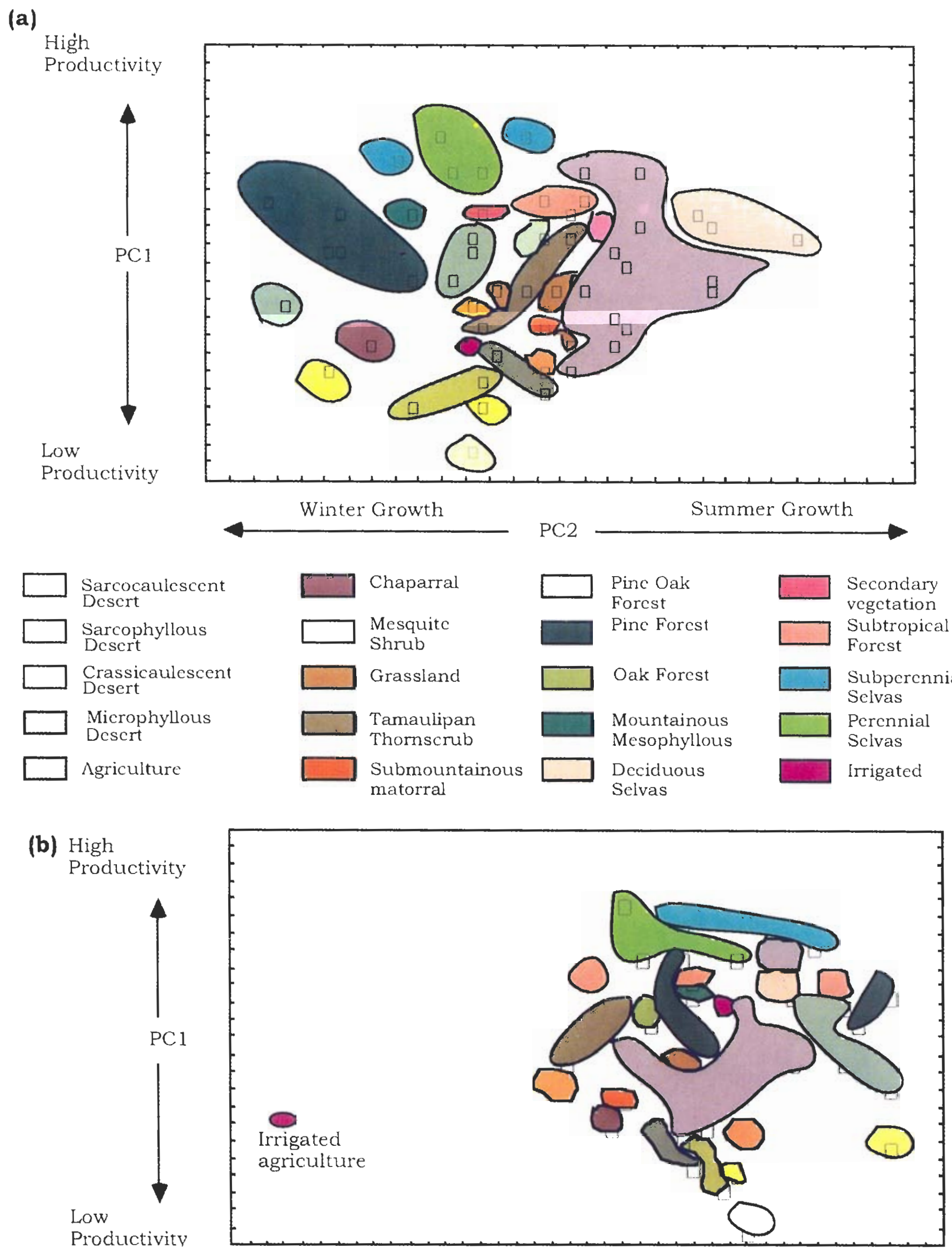

Figure 4 Feature space plot evaluated for class means in (a) PC1 and PC2 and (b) PC I and PC3.

identify agricultural areas that are irrigated in May. In this analysis, landscape units represent primarily ecosystems at the biome level due to the scale of GVI observations. These 60 spectral classes also can be

Table 1 Land-cover and vegetation types reported on INEGI map associated with the unsurpervised classification of Mexico.

CLASS	LAND COVER	DESCRIPTION	OTHER TERMINOLOGY	Area [10^3 ha]	% Mexico area
1	Sarcocaulescent desert	Desert vegetation, dominated by large sarcocaulescent trees (*Bursera microphylla* and *Jatropha cinerea*) with succulent plants (*Idria columnaris*), evergreen shrubs (*larrea tridentata*), and deciduous shrubs (*Jatropha cuneata*).	Desert, cactus scrub, matorral xerofilo	6,761	4
2	Sarcophyllous desert	Desert vegetation, dominated by leaf sarcophyllous succulent plants (*Agave*) and perennials shrubs (*Franseria sp, Yucca valida*).	Desert, matorral rosetofilo costero, matorral desertico rosetofilo	9,629	5
3	Crassicaulescent desert	Desert vegetation, dominated by large cactus (stem-succulent) (*Carnegia gigantea, Ferocactus wislizenii*) cylindropuntia and platyopuntia, and perennial shrubs (*Cercidium microphyllum*).	Desert, matorral crasicaule, cardonal	12,472	7
4	Microphyllous desert	Desert vegetation, dominated by ephemeral herbaceous species (growing winter season) and a low density of perennial plants. *Larrea tridentata* and *Franseria dumosa*.	Semideserts, matorral desertico microfilo, matorral espinoso	10,390	6
5	Agriculture	Rainfed agriculture.		51,498	28
6	Chaparral	Plant community of shrubs and scrubs developed in a Mediterranean climate with species resitant to fire (*Quercus sp, Adenostoma sp*) and annual grasses (*Arctostaphylos sp* and *Cercocarpus sp*).		1,628	1
7	Mesquite shrub	Semidesert vegetation dominated by trees with small leaves, generally mesquite (*Prosopis sp*), but *Acacia sp* and *Cercidium sp* are also common.	Woodland, savanna, mesquite-grassland	4,555	2
8	Grassland	Annual grasses.	Pastizal, zacatonal,sabana	10,915	6
9	Tamaulipan thornscrub	Semidesert shrubs and low forest formations, with thorny and deciduous species (*Acacia sp, Cercidium sp, Leucophyllum sp, Prosopis sp*).	Thorn forest, thorn woodland, matorral espinoso tamaulipeco	9,608	5
10	Submountainous matorral	Semidesert shrubs and deciduous woodlands (*Helietta parvifolia, Neopringlea integrifolia, Cordia boissieri, Acacia sp and Leucophyllum sp*). Considered a transition zone between semidesert matorrals, deciduous selvas[a], and oak forest.	Thorn woodland, matorral, matorral submontano, selva baja espinosa.	3,033	2
11	Pine oak forests	Conifer temperate forest dominated by species of pine (*Pinus sp*) and oaks (*Quercus sp*). Characteristic species vary with the geographic region.	Boreal forest, bosque de coniferas, pinar encinar	10,737	6
12	Pine forests	Conifer temperate forest dominated by pines.	Conifer forest, pinar, bosque de pino	7,713	4
13	Oak forests	Temperate forest dominated by oaks.	Encinar, bosque semihumedo de montana	2,073	1
14	Mountainous mesophyllous forests	Temperate deciduous forest on mesic hillsides dominated by deciduous broad-leaved species (*Engelhardtia mexicana, Juglans olachana, Liquidambar styraciflua,* and *Ostria virginiana*) and with evergreen (*Pinus sp*) species dominating the lower strata.	Cloud forest,montane rain forest, temperate deciduous forest, mountain mesic forest, bosque mesofilo de montana	3,158	2
15	Deciduous dry selva	Selva in warm dry climates with highly deciduous (6-8 months of growing season) and semideciduous species (*Bursera sp, Lysiloma sp, Jacaratia mexicana, Ipomoea sp, Pseudobombax sp, Cecropia sp, Cendrela sp, etc*) and with a dense thicket-like understory.	Deciduous seasonal forest, tropical deciduous forest, selva baja caducifolia, bosque tropical deciduo	12,267	7
16	Second growth vegetation	Vegetation that results from secondary succesion in areas which have been cleared for agricultural or grazing purposes.		2,153	1
17	Subtropical forests	Subtropical thorny shrubs, matorrals, and forests that share characteristics of each. Considered a transition zone between temperate forest and matorrals. Characteristic species are *Ipomonea sp, Bursera sp, Eysenhardtia polystachia* , and *Acacia sp*.	Semi-evergreen seasonal forest,tropical deciduous forest, bosque tropical subcaducifolio	5,062	3
18	Perennial selvas	Three-storied selva, in tropical climates, dominated almost exclusively by perennial species with straight, unbranched, buttressed trunks rising 50-60 m from the forest floor (*Aspidosperma megalocarpon, Brosinum alicastrum, Dialum guianense, Terminalia amazonia, Swietenia macrophylla, Vochysia guatemalensis, Alchornea latifolia, Alibertia edulis, Belotia cambellii Bumelia persimilis, Bursera simaruba*). The second stratum contains a continuous canopy of branched trees of 25-40 m. The third stratum contains small trees 10-20 m tall.	Rain forest, tropical evergreen forest,selva alta perennifolia, bosque tropical perennifolio, selva alta siempre verde, selva ombrofila siempre verde	9,216	5
19	Subperennial selvas	Selva with a dominance of subperennial trees and a well-defined dry season, and with less overdue precipitation. Superficially , it has similar composition as perennial selvas, but has only two and ocassionally one layer of trees. "Dominant" species are *Astronium graveolens, Bernoullia flammea, Brosimum alicastrum, Bumelia persimilis, Ceiba pentandra*.	Montane rain forest, semi-evergreen seasonal forest, bosque tropical subcaducifolio, bosque deciduo semihumedo	8,780	5
20	Irrigated agriculture	Irrigated agricultural lands.		2,962	2

[a]*Selva* is a term in Spanish which distinguishes between the highly diverse communities of trees developing in the lowlands, in contrast to bosque that describes the communities of trees in the highlands and mountains.

specifically related to 20 vegetation and land-cover classes defined a *priori* via the INEGI (1980) map. Thus, statistically valid areal estimates (Table 1) and a map depicting the distribution of the resulting vegetation and land-cover classes can be obtained (Fig. 5).

The results of vegetation and land-cover mapping (Fig. 5) shows that patterns of vegetation distribution are highly consistent with those observed in multitemporal GVI monthly variation and PCA. Substantial differentiation can be obtained by classifying contrasting phenological vegetation types (e.g., conifers, rain forests and deserts), but vegetation and land-cover classes are less evident when they occur within similar phenological groups (i.e., semidesert type). PC3 also allows the identification of highly contrasting phenological zones such as irrigation areas that probably would be less evident without multitemporal information.

Results of the classification also show that most of the Mexican landscape can be classified as "natural" (69%) by summing the classes dominated by natural vegetation. The remaining portion is classified as cultural (agriculture, irrigation, and secondary growth), most of which (28% of the total area of Mexico) is predominantly agriculture. The highest proportion of natural landscape categories is in deserts, deciduous selvas, grasslands, and conifers, each of which occupies only about 6 and 7% of the total area in Mexico (Table 1).

The characteristic GVI variation of each class during the year defines a multitemporal spectral signature for each ecosystem or land-cover unit identified in this analysis (Fig. 6). Ecological information that is not evident without temporal analysis can be extracted from these signatures, and when combined with PCA which distinguishes the classes, allows the characterization of the landscape in several ways not previously possible (Figs. 2e, 2f & 4). Phenological attributes such as peak and onset of greenness, levels

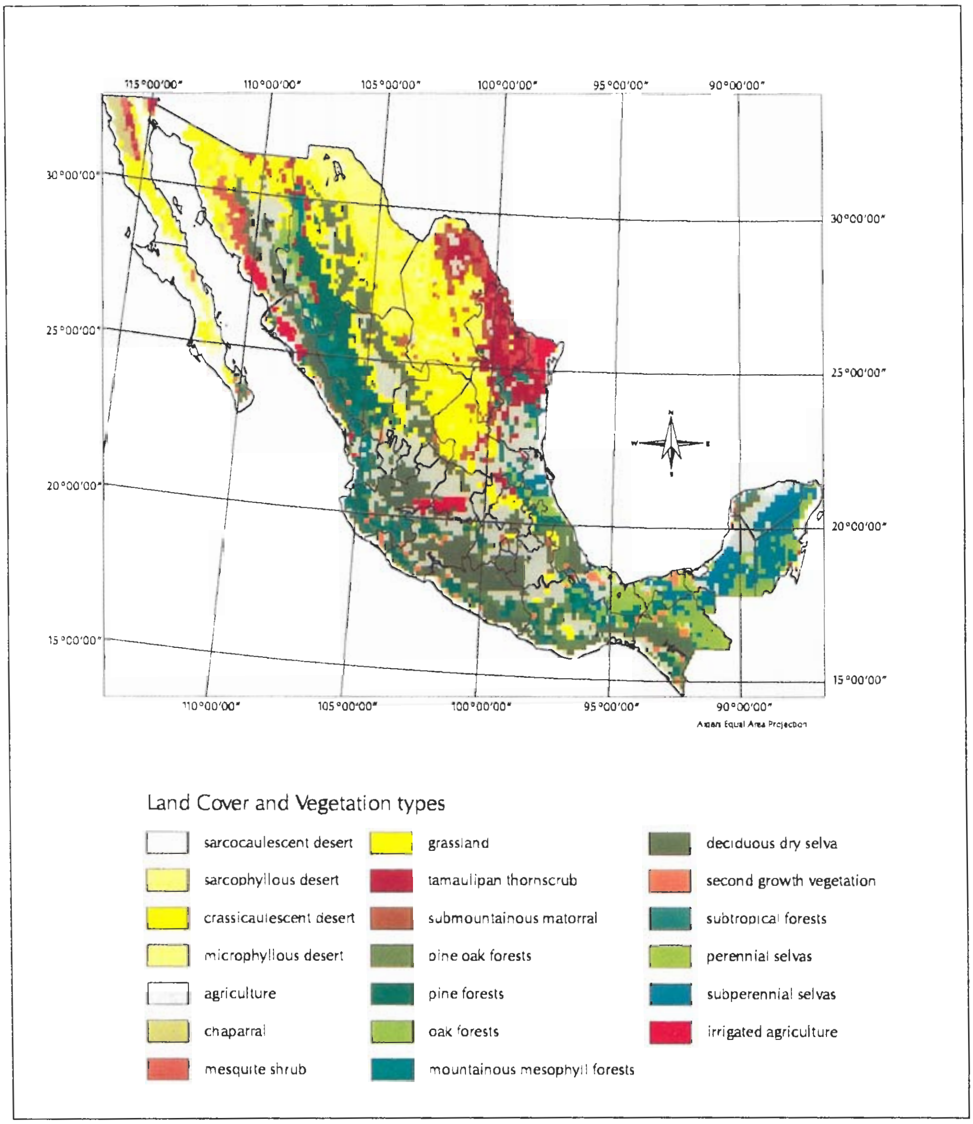

Figure 5 Land cover and vegetation types.

of minimum and maximum photosynthetic activity, and beginning and duration of the growing season along with seasonality measures, can be obtained for specific locations (Fig. 2, Table 2). Subsequently, all of these attributes can be used as multivariate variables to classify landscape units in ecological terms.

However, not all of the phenological information derived with this analysis is completely independent. Correlation analysis among phenological variables showed that phenological attributes can be redundant in capturing their respective spatial patterns of distribution (Table 3).

Squared correlation coefficients among phenology variables showed that considerable variance (67%) can be explained between vegetation productivity (PC1) and maximum and minimum photosynthetic levels, as well as with the photosynthetic level at peak. This reinforces the idea of PC1 as a vegetation productivity component. More than 80% of the variance in both photosynthetic levels at peak and onset can be explained if the maximum GVI registered is used rather than combining PCA and the unsupervised classification. However, maximum GVI values during the year give no indication of the months in which these occur.

Photosynthetic levels of vegetation activity, particularly peak and onset of the growing season, are

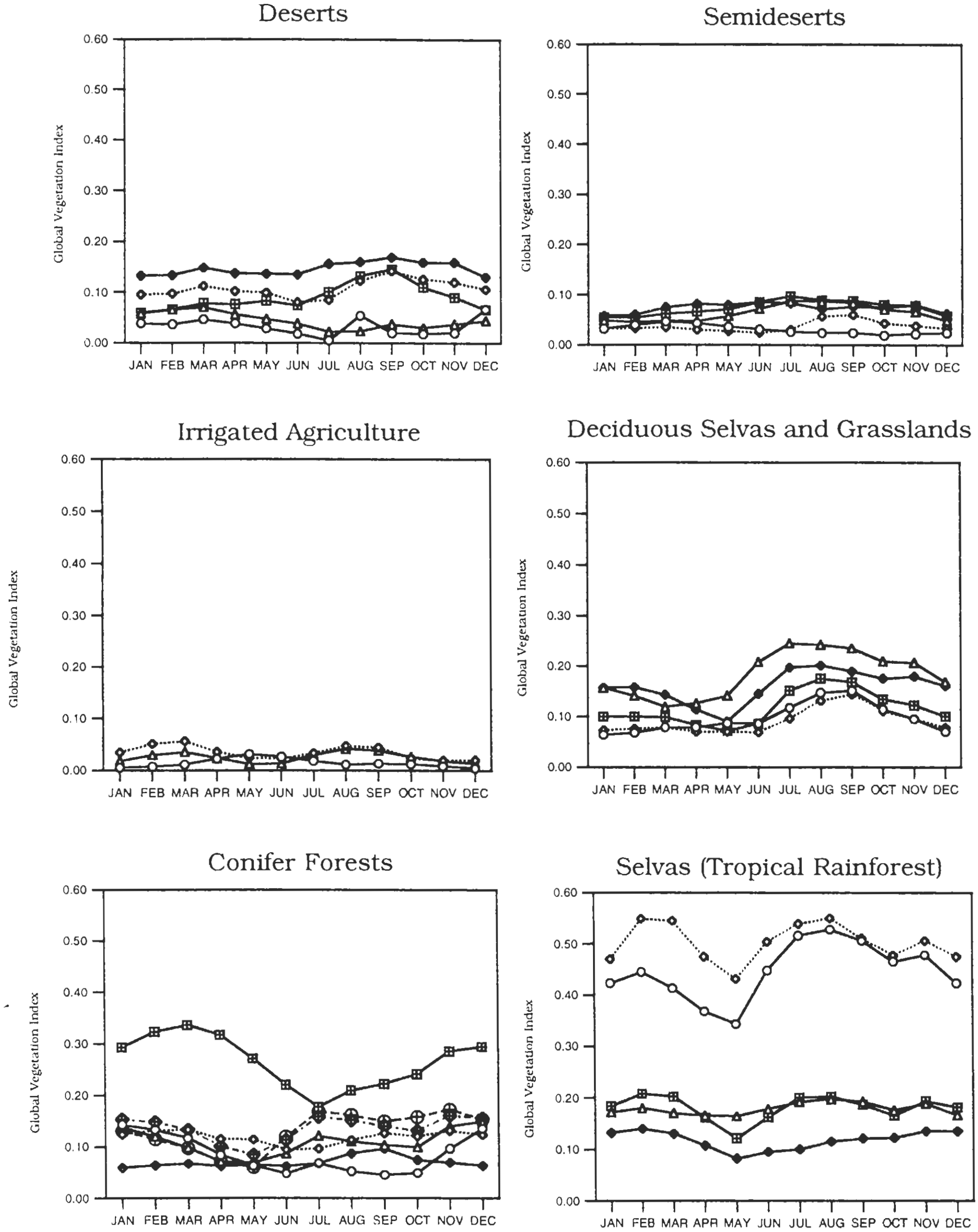

Figure 6 Spectral signatures for individual classes identified with ISODATA. Individual spectral classes (lines within each group) are associated with land covers and vegetation types and grouped on a phenological basis.

Table 2 Phenological classification of vegetation activity using multitemporal GVI and principal component analysis.

Phenological Characterization of vegetation in Mexico* based on Multitemporal GVI imagery and PCA	
Phytophenological attribute:	NDVI definition:
1) Minimum level of photosynthetic activity	Minimum GVI value
2) Maximum level of photosynthetic activity	Maximum GVI value
3) Beginning of growing season	Month at which "Onset" was recorded
4) Peak of growing season	Month at which "Peak" was recorded
5) Photosynthetic level at the beginning of the growing season	Onset (GVI) value
6) Photosynthetic level at the peak of the growing season	Peak (GVI) value
7) Annual vegetation productivity index	PC1 value
8) Seasonality index for natural vegetation	PC2 value
9) Seasonal indexes for nonnatural vegetation (Agriculture)	PC3, PC4 and PC5 values

**Modified from Lloyd (1991)*

Table 3 Pearson's correlation coefficients (squared) for phenological variables derived from multitemporal GVI imagery and principal component analysis in Mixico.

	1	2	3	4	5	6
Vegetation Productivity	1.00					
Vegetation Seasonality	0.240	1.00				
Maximum photosynthetic level	0.672	0.058	1.00			
Minimum photosynthetic level	0.672	0.017	0.436	1.00		
Photosynthetic level at onset	0.518	0.032	0.828	0.348	1.00	
Photosynthetic level at peak	0.672	0.068	0.884	0.462	0.792	1.00

highly correlated with each other and with vegetation productivity, but seem to be highly independent from seasonality measures (Table 3). PC2 is completely independent information about vegetation phenology. None of the other phenological variables are correlated with vegetation seasonality, indicating that PCA gives real (not apparent) variation in seasonal vegetation (Fig. 7). The correlations among the phenological variables can be identified visually by their respective spatial patterns (Fig. 2).

The probable causal factors of temporal and spatial variations of individual classes, and consequently of landscape units, can be established using additional information such as climate and topographic variables. If such associations were found, the spatial patterns of landscape units could be predicted by a GIS database, with the results of the multitemporal analysis used as a valuable source of temporal and spatial vegetation patterns for Mexico. Such an analysis and GIS implementation is currently in progress.

Conclusions

In this study, principal component analysis of multitemporal GVI images of Mexico summarized the vegetation variation in the landscape. Current improvements in the acquisition and resolution of multitemporal vegetation data, via remote sensing, will continue to help alleviate the problem of lack of ecological data for the country. With the application of PCA on multitemporal (LAC, GAC or GVI) data, several phenologically meaningful components can be obtained that represent the total annual variation of vegetation dynamics. Since PCA captures nearly all of the temporal variation in the multitemporal GVI dataset, it seems well suited for the seasonal vegetation analysis of the landscape of Mexico. PCA also offers several advantages in subsequent multivariate analysis (i.e., identifying classes) since the new variables obtained are statistically independent. Variance reduction techniques also can significantly reduce the CPU time in calculations as well as disk space.

The new components derived from this analysis can be interpreted as phenological variables and used to characterize the landscape in terms of productivity, seasonal variations in natural vegetation, and seasonal variations in "non-natural" vegetation types (e.g., agricultural lands). Additionally, the interpretation of multitemporal signatures for every class allows the characterization of every landscape unit in phenological attributes. The use of spatial classifiers in the definition of spectral classes also allows the capture of spatial heterogeneity of every landscape unit.

Since PCA (as with other variance-reduction techniques) is highly scene dependent, this interpretation of components and classes is valid only for the landscape in Mexico as described here. However, similar interpretations can be obtained for other regions.

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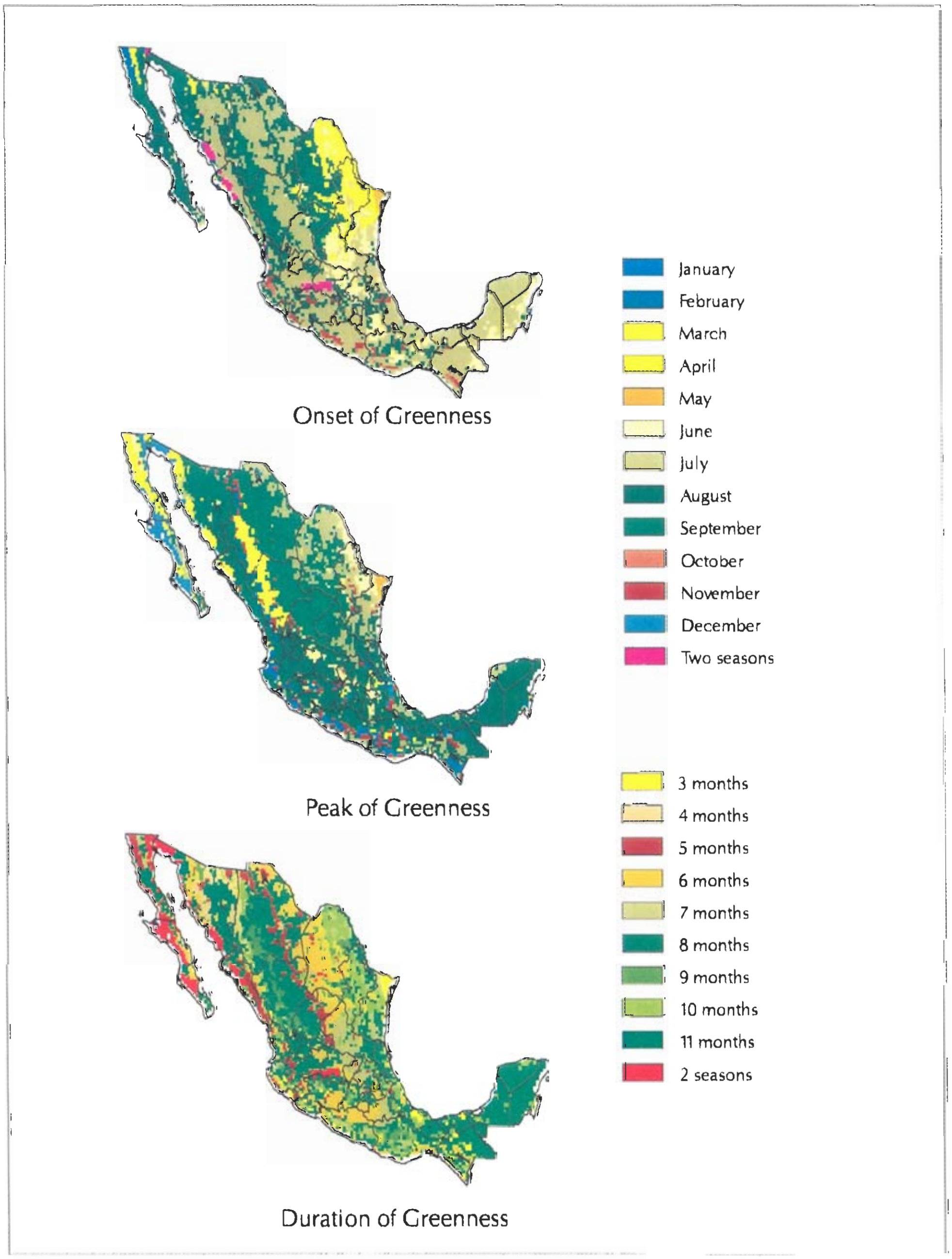

Figure 7 Seasonal variation of vegetation activity in Mexico. (a) onset, and (b) peak of growing season, (c) duration of growing season identified with GVI.

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