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

Franz Mora*
Department of Forestry, University of Illinois, Urbana, IL 61820, U.S.A.

Louis R. Iverson
USDA Forest Service, 359 Main Road, Delaware, OH 43015, U.S.A.

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.

* Current address: Center for Advanced Land Management Information Technologies, University of Nebraska at Lincoln, 113 Nebraska Hall, P.O.Box 880517, Lincoln, NE 68588-0517, U.S.A.
conversion, better decision making is needed for implementation. Deforestation rate approaching 10% of tropical forested land is evident in Mexico (Inventario Nacional Forestal 1991). Additionally, non-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 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 (INEGI 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 scale 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 is also necessary to develop a framework that integrates temporal variations and spatial heterogeneity of ecological landscape features. A landscape ecological classification defines such a framework, and it is more robust 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 observation, 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 compositing technique (Ouring et al. 1989). Image compositing 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; (2) Global Area Coverage (GAC), with 1 by 4 km at nadir; and (3) Local Area Coverage (LAC), with 1 by 1 km cell size at nadir (Kidwell 1990). Different cell sizes in AVHRR products allow analysis of temporal trends of ecological variables associated with those 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 1988; Goward et al. 1991; Hastings and Emery 1992; Holben 1986; Roller and Colewalt 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; Takeishi 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 (Eidebink and Hass 1992). Practically, the imaging frequency and compositing process makes it possible to describe regional vegetation on a seasonal (phenological) basis (Lloyd 1993).

Environmental applications of AVHRR include land-cover mapping, vegetation dynamics studies, tropical forest monitoring, fire risk assessment, vegetation production and biophysical parameter estimation (Ehrlrich 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 (Ehrlrich 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 Fuke
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) 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 (Efclien
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
necessary 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) through 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 40 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 "green cover" or spurious sensor artifacts,
our examination 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
value of 65) to represent the data, from no vegetation
productivity to maximum vegetation productivity, in
4-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
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 minimum monthly GVI score) for each pixel; and (2) minimum photosynthetic level (or maximum 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 parallel-leveled 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 corresponding 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 their 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 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
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 bimodal in nature (Fig. 3).

Figure 2 Phenological variation derived from 12 monthly GVI scores (scaled from 0 to 1). (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 Peninsula 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; Coward 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
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 irrigated agriculture). Lower values are mostly associated with seasonal vegetation that reaches peak of greenness from November to April i.e., coniferous forests. Thus, the minimum 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,....
<table>
<thead>
<tr>
<th>CLASS</th>
<th>LAND COVER</th>
<th>DESCRIPTION</th>
<th>OTHER TERM/LOGO</th>
<th>Area [%]</th>
<th>% Mexico</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Semiarid/mesic desert</td>
<td>Desert vegetation, dominated by large perennial grasses (Baccharis salteri) and Aizoaceae shrubs associated with halophytic species (Halocnemum strobilaceum)</td>
<td>Desert, desert scrub, chilean scrub</td>
<td>5,761</td>
<td>4</td>
</tr>
<tr>
<td>2</td>
<td>Semiarid/mesic desert</td>
<td>Desert vegetation, dominated by leaf succulent/saprophytic plants (Agave) and perennial herbs (Paronychia sp., P. frutescens)</td>
<td>desert, montane scrub, arid shrubland</td>
<td>9,049</td>
<td>5</td>
</tr>
<tr>
<td>3</td>
<td>Coniferous forest</td>
<td>Desert vegetation, dominated by large agaves (Agave americana)</td>
<td>desert, montane conifer, arid conifer</td>
<td>12,472</td>
<td>7</td>
</tr>
<tr>
<td>4</td>
<td>Mosaic desert</td>
<td>Desert vegetation, dominated by ephemeral herbaceous species (growing winter season) and a low density of perennial plants, (Amaranthus and Paronychia sp.)</td>
<td>desert, montane mosaic, arid mosaic</td>
<td>10,390</td>
<td>6</td>
</tr>
<tr>
<td>5</td>
<td>Agriculture</td>
<td>Irrigated agriculture</td>
<td>Desert, arid irrigated, arid wetland</td>
<td>51,498</td>
<td>28</td>
</tr>
<tr>
<td>6</td>
<td>Chaparral</td>
<td>Desert vegetation, dominated by leaf succulent/saprophytic plants (Agave) and perennial herbs (Paronychia sp., P. frutescens)</td>
<td>desert, montane chaparral, arid chaparral</td>
<td>6,761</td>
<td>4</td>
</tr>
<tr>
<td>7</td>
<td>Mesquite shrubland</td>
<td>Desert vegetation, dominated by mesquite-baja espinosa, an acacia type with a dense baja deciduous forest, composed of (Acacia, Prosopis sp., P. tamariscifolia)</td>
<td>desert, mesquite woodland, arid mesquite woodland</td>
<td>9,629</td>
<td>5</td>
</tr>
<tr>
<td>8</td>
<td>Grassland</td>
<td>Desert vegetation, dominated by large succulent shrubs (Atriplex hymenelytra, A. stricta, A. salicaria) and with evergreen (Prosopis sp., Acacia sp.) species dominating the lower strata</td>
<td>desert, montane grassland, arid grassland</td>
<td>4,555</td>
<td>3</td>
</tr>
<tr>
<td>9</td>
<td>Sarcocaulic Desert vegetation, dominated by large succulent shrubs (Atriplex hymenelytra, A. stricta, A. salicaria) and with evergreen (Prosopis sp., Acacia sp.) species dominating the lower strata</td>
<td>desert, montane grassland, arid grassland</td>
<td>10,737</td>
<td>6</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>Saddleback Desert vegetation, dominated by large succulent shrubs (Atriplex hymenelytra, A. stricta, A. salicaria) and with evergreen (Prosopis sp., Acacia sp.) species dominating the lower strata</td>
<td>desert, montane grassland, arid grassland</td>
<td>10,970</td>
<td>6</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>Oak-Scrub</td>
<td>Desert vegetation, dominated by large succulent shrubs (Atriplex hymenelytra, A. stricta, A. salicaria) and with evergreen (Prosopis sp., Acacia sp.) species dominating the lower strata</td>
<td>desert, montane oak, arid oak forest</td>
<td>10,476</td>
<td>7</td>
</tr>
<tr>
<td>12</td>
<td>Pine-Scrub</td>
<td>Desert vegetation, dominated by large succulent shrubs (Atriplex hymenelytra, A. stricta, A. salicaria) and with evergreen (Prosopis sp., Acacia sp.) species dominating the lower strata</td>
<td>desert, montane pine, arid pine forest</td>
<td>10,167</td>
<td>6</td>
</tr>
<tr>
<td>13</td>
<td>Subarid/Desert shrubland and low forest formations, with thorny and deciduous species (Acacia, Paronychia sp., Digitalis sp.)</td>
<td>desert, montane scrub, arid shrubland</td>
<td>9,115</td>
<td>5</td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>Oak-Forest</td>
<td>Desert vegetation, dominated by large succulent shrubs (Atriplex hymenelytra, A. stricta, A. salicaria) and with evergreen (Prosopis sp., Acacia sp.) species dominating the lower strata</td>
<td>desert, montane oak, arid oak forest</td>
<td>2,857</td>
<td>1</td>
</tr>
<tr>
<td>15</td>
<td>Desert shrubland and low forest formations, with thorny and deciduous species (Acacia, Paronychia sp., Digitalis sp.)</td>
<td>desert, montane scrub, arid shrubland</td>
<td>3,118</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>16</td>
<td>Evergreen seasonal forest</td>
<td>Desert vegetation, dominated by large succulent shrubs (Atriplex hymenelytra, A. stricta, A. salicaria) and with evergreen (Prosopis sp., Acacia sp.) species dominating the lower strata</td>
<td>desert, montane evergreen forest, arid evergreen forest</td>
<td>12,267</td>
<td>7</td>
</tr>
<tr>
<td>17</td>
<td>Semi-deciduous forest</td>
<td>Desert vegetation, dominated by large succulent shrubs (Atriplex hymenelytra, A. stricta, A. salicaria) and with evergreen (Prosopis sp., Acacia sp.) species dominating the lower strata</td>
<td>desert, montane semi-deciduous forest, arid semi-deciduous forest</td>
<td>10,167</td>
<td>6</td>
</tr>
<tr>
<td>18</td>
<td>Subperennial selvas, Selva with a dominance of subperennial trees and a well-defined dry season, and Montane rain forest, semi-deciduous forest, alpine rain forest</td>
<td>desert, montane scrub, arid shrubland</td>
<td>8,780</td>
<td>5</td>
<td></td>
</tr>
<tr>
<td>19</td>
<td>Subtropical forests</td>
<td>Desert vegetation, dominated by large succulent shrubs (Atriplex hymenelytra, A. stricta, A. salicaria) and with evergreen (Prosopis sp., Acacia sp.) species dominating the lower strata</td>
<td>desert, montane scrub, arid shrubland</td>
<td>5,062</td>
<td>3</td>
</tr>
</tbody>
</table>
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
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.
Phenological Characterization of vegetation in Mexico* based on Multitemporal GVI imagery and PCA

Phytophenological attribute: Phytophenological attribute: NDVI definition:
I) 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 PC3, PC4 and PC5 values

(Agriculture)


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

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vegetation Productivity</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Vegetation Seasonality</td>
<td>0.240</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Maximum photosynthetic level</td>
<td>0.672</td>
<td>0.058</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Minimum photosynthetic level</td>
<td>0.672</td>
<td>0.017</td>
<td>0.436</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Photosynthetic level at onset</td>
<td>0.518</td>
<td>0.032</td>
<td>0.828</td>
<td>0.348</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>Photosynthetic level at peak</td>
<td>0.672</td>
<td>0.068</td>
<td>0.884</td>
<td>0.462</td>
<td>0.792</td>
<td>1.00</td>
</tr>
</tbody>
</table>

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.

Acknowledgments

The authors gratefully acknowledge Elizabeth Cook, Onset of Greenness

Peak of Greenness

Duration of Greenness

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.
Susan Egen-McIntosh and Zuliang Zhu for improving the quality of the manuscript at early stages. Special thanks to the Illinois Natural History Survey for providing the equipment and facilities to support this research. This research was conducted while the first author held a Fulbright-CONACYT-IIE scholarship for his M.S. degree at the Department of Forestry, University of Illinois, Urbana-Champaign. This research was partially funded by the Tinker foundation of the University of Illinois at Urbana-Champaign.

References


Construction Engineering Research Laboratory. Global GRASS I, CD of 50 global coverage maps. Cook College Remote Sensing Center, Rutgers University, New Brunswick, N.J.


