Vegetation Biodiversity using Remote Sensing

Landscape Ecology and Diversity Patterns in the Seasonal Tropics from Landsat TM Imagery

Introduction
Landsat Thematic Mapper (TM) imagery was used to analyze patterns of landscape diversity in the seasonal tropical forests of northeastern Guatemala. TM radiance and the radiance coefficient of variation (CV) were significant in discriminating land-cover types. Cluster analysis of TM4, TM5, and TM7 radiance produced six distinct types of land-cover. Green leaf biomass from TM4 and canopy closure and degree of senescence from TM5 and TM7 represent the most important variables in discriminating between land-cover types in the uplands and the lowland swamps respectively. Patterns of landscape diversity reflected in three landscape indices were also examined: the number of land-cover types (LCT), the Shannon-Weaver index of landscape evenness (S-W), and a topographic index (TI).

Primary Objective
To demonstrate that TM analyses, without extensive field data, provide valuable information on landscape diversity patterns to aid conservation and development plans when time and resources do not permit intensive field studies.

Background
TM4 (0.76-0.90 μm) or TM3 (0.63-0.69 μm) reflectance is shown to measure vegetation density relating to leaf area, green-leaf biomass, and photosynthetic activity. TM3 is related to green-leaf biomass due to its inverse relationship with chlorophyll content. TM5 (1.55-1.75 μm) and TM7 (2.08-2.35 μm) have a longer wavelength infrared reflectance that is inversely related to moisture, and can provide a measure of standing dead biomass, or senescent woody biomass because the biomass is drier than live, photosynthetically active tissue. These bands provide a measure of canopy closure, whereby reflectance increases as more forest floor is detected from space.
Study Area
The study area is located in the northeastern corner of the Department of El Peten, in the Republic of Guatemala (picture below). It is typical of tropical karst regions, with conical hills and closed depressions. Rainfall is highly variable, both spatially and temporally, and averages between 1200 to 2000 mm annually, over half of which falls between June and September. The four most common forest associations typical for the study area, beginning in the bajo (karst depression) center and extending to the top of a conical karst hill, are:

Tintal – a low (5-11 m), open swamp forest with palms in the understory
Escobal – a slightly higher swamp forest with palms in the understory
Botanal – a medium-high (15-25 m) swamp forest on better drained soils with many isolated tall trees
Zapotal – a high (25 m with isolated trees to 40 m) multi-tiered, closed canopy forest

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![Map of the study area in northern El Peten, Guatemala, Central America. Shown are the boundary of the Maya Biosphere Reserve (region above dotted line, which includes the buffer zone), the location of the Landsat TM quarter scene used in the analysis (large box), and the three test sites (small boxes): A = Dos Lagunas; B = Bajo Azucar; C = Holmul.](image-url)
Methods
Three sites were selected (Dos Lagunas, Bajo Azucar, and Holmul) and analyzed with different geomorphology and vegetation distributions to sample a variety of natural landscape types with as little human disturbance, clouds, or haze. A dry-season Landsat TM image was selected because of suspected differences between forest types in the dry/wet season due to seasonal, drought-induced senescence. They used Microimages’ Map and Image Processing System (MIPS), for Landsat image processing, principal components analysis (PCA) and the first step in the cluster analysis (k-means classification), SAS for the centroid clustering, discriminate analysis (DA), analysis of variance (ANOVA), and the correlation and regression analyses. The three indices of landscape diversity were examined: LCT, S-W, and TI. Land-Cover Type was considered absent in a cell when it accounted for <2% of the total number of pixels within that cell. The Shannon-Weaver index was used as a measure of evenness. Expressed by

\[ H = -\sum p_i \times \ln p_i \]

Where \( p_i \) is the probability of finding a land-cover type in a cell. The topographic index is equal to the sum of the area of each land-cover type in a cell multiplied by its topographic rank, and divided by the total area of the cell. Where 1 ranks the lowest and 6 ranks the highest, or most rich, along the topographic gradient.

Results
The results of PCA indicate that near-infrared reflectance, as measured by TM4, is the main source of variability in the imagery at the pixel level. TM4 is highly correlated \((r = 0.99, P < 0.0001)\) with PC1, accounting for 59.8% of the total variance. TM5 is the second most highly correlated \((r = 0.94, P < 0.0001)\) with PC2, accounting for 26.4% of total variance. TM7 is the third most highly correlated \((r = 0.35, P < 0.0001)\) with PC1 and \((r = 0.62, P < 0.0001)\) with PC2, accounting for 8.1% of total variance. Dos Lagunas has the most uneven distribution of vegetation types \((S-W = 0.53, TI = 4.41)\), Bajo Azucar has the highest TI \((S-W = 0.62, TI = 4.62)\) and Holmul has the most even distribution \((S-W = 0.89, TI = 3.81)\).
Identifying Conservation-Priority Areas in the Tropics: A Land-Use Change Modeling Approach

Introduction
There are methods that allow identification of conservation-priority area that have been proposed. Two major types of information are necessary for setting conservation priorities: the conservation value of an area and its vulnerability. An analysis of the overall pattern of land use in a given area could be a guide to identifying vulnerable areas. In the Old World tropics, 80% of the countries have lost over half their wildlife habitat, and 65% of primary forest habitat has been lost in tropical Asia. They propose a method for identifying conservation-priority areas based on a predictive, land-use change modeling approach. Unprotected natural areas most susceptible to land-use change by virtue of their geophysical and socioeconomic characteristics can be ranked as the highest-priority areas for in-depth field inventories of biodiversity distribution.

Objectives
To use a geographic information system and spatially explicit modeling to:
- Examine patterns of land-use change in Arunachal Pradesh
- Examine the correlation of land-use patterns with biogeophysical characteristics
- Predict areas most susceptible to future deforestation and biodiversity loss based on geophysical and developmental variables

Study Area
The state of Arunachal Pradesh (lat 26°-29° N, long 91°-97° E), which covers 83,743 km², and has one of the richest floras in the world. It has three main forest types:
- Tropical wet-evergreen forests, occurring up to elevations of 900 m
- Subtropical forests, located between 800 and 1900 m
- Pine forests, extending into both the subtropical and temperate belts between 1000 and 1800 m
Methods
The source for the 1988 land-cover and land-use information was a series of 1:250,000-scale thematic paper maps prepared by visual interpretation of false-color composites of satellite imagery. Landsat TM imagery was from 1987 and IIRS LISS-II imagery was from 1988. The images had digitizing completed in these areas:

- **Land cover** - evergreen forests, deciduous forests, degraded forests, forest blinks, wastelands, water, and snow
- **Land use** - forest plantations, shifting agriculture, grazing land, other agriculture, and towns
- **District boundaries**, towns, roads, rivers, and reservoirs

Maps were digitized in a vector format with the GIS package CAMRIS. The coverage's were estimated to have a positional accuracy of 60 m based on the errors introduced during digitizing and importing. A U.S. Geological Survey GTOPO30 elevation map was used to generate a slope map and an aspect map, each with resolution of 1 km² per cell. They then converted the vector coverage's into raster grids, in preparation for the GEOMOD2, and reclassified the 1988 land use map into three categories: Forest, disturbed, and other. GEOMOD2 simulation then selected forested grid cells to convert to the disturbed category according to two rules:

- Specify the quantity of forest disturbance
- Prioritize locations with the greatest risk of disturbance

GEOMOD2 computed the risk of disturbance by comparing the 1988 land-use map to each of six geophysical attributes: Elevation, slope, aspect, buffer around towns, buffer around roads, and buffer around rivers and reservoirs. Finally, a risk-of-disturbance map was created.

Results
Areas closer to roads and towns have fewer evergreen forests, whereas areas more than 6 km from roads or towns are about 70% forested. It is projected that 50% of the state’s 1988 forests will be lost by 2021, based on exponential growth of the human population and resulting resource use.
Remote Sensing of Vegetation, Plant Species Richness, and Regional Biodiversity Hotspots

Introduction
Diversity estimation and mapping techniques take advantage of the relationship between species richness and habitat diversity, where species richness increases as environmental heterogeneity increases at a variety of scales. Mapping of diversity is accomplished by analyzing variation of some spectral signal, and correlation this variation with measures of landscape or taxa diversity. Results obtained are compared by analyzing: Normalized difference of vegetation index (NDVI) variability and a satellite-derived vegetation map with ground-based measures of species richness.

Goals
To analyze species diversity and landscape heterogeneity in an arctic landscape by:
- Mapping the vegetation of the Hood River Region of the Central Canadian Arctic
- Developing techniques to predict and map variation in plant species richness using remote sensing
- Assessing and comparing the techniques used to estimate species richness

Regional variation in plant species richness was estimated by:
- Analyzing variation in NDVI measures obtained from Landsat Thematic Mapper (TM) data
- Analyzing the regional vegetation map created for this study in relation to intensive ground-based measures of plant species richness and plant community composition

Study Area
The Hood River area is just north of the Arctic Circle in the central Canadian Arctic. The Bear-slave Uplands consist of low topographic relief, rolling granitic hills, and shallow, discontinuous cover of glacial tills dissected by numerous lakes and drainage basins. The Bathurst Lowlands consist of greater relief, extensive marine deposits, and non-acidic bedrock outcrops.
Methods
Image and field sampling areas were chosen in this study with the goal of characterizing species richness and landscape heterogeneity within a roughly 0.5 km$^2$ area to better understand and map richness patterns at the mesoscale. Among-pixel variation was sampled at the same scale as the field-measured species richness and community date. The relationships between richness estimated by variation among pixels, vegetation type diversity, and ground-measured species richness were all determined from the same pixel areas and species richness mapping was based on these relationships.

Methods – Vegetation studies
17, 0.5 km$^2$ study sites at Hood River valley were selected. Species richness was measured within each site by determining the vascular plant species present within a set of eight randomly placed 100 x 3 m plots. The sampling was focused along the riparian corridor because of easier river access, and all major regional vegetation types can be found along the corridor.

Methods – Vegetation Map
A land cover map was derived from a supervised classification of Landsat TM scene covering the area. A single Landsat TM scene (path 46 row 13) was used. The image was atmospherically corrected using dark object subtraction, converted to reflectance and calibrated based on scene acquisition date and sun angle, and georeferenced. TM bands 1-5 and 7 were used in a maximum likelihood algorithm for supervised classification with ground-truthed target areas used for interpretation. Training sites for the supervised classification were chosen from homogeneous areas for which detailed vegetation descriptions were available.

Methods – Richness estimates
A weighting factor was determined from field samples of vascular plant richness and used in conjunction with the classified vegetation map to remotely estimate plant richness. Detailed floristic data for each study site enabled weighting the land cover types based on relative vascular richness within a type. The weighting factors were determined by dividing the sum of potentially occurring species of a cover type by the sum from the least species-rich vegetation type. Richness values for each 500-pixel area were determined by multiplying the number of pixels of each class by the weighting factor and determining the mean value of the 500-pixel area. This data was then used in regression analysis to determine the relationship between measured and estimated species richness.
Methods – NDVI variability
An NDVI image was created using TM data from the peak of the growing season and used in the analysis of variation in NDVI. Non-positive values in the NDVI image were set to zero, this removed some of the variance associated with non-vegetated surfaces. Regression analysis was used to determine the relationship between measured species richness, NDVI variability, and weighted vegetation type abundance of the 17 intensive study sites.

Methods – Richness Mapping
Species richness estimates were determined for a central pixel of each 500-pixel area on the NDVI image and vegetation map using a 25 x 20 pixel filter and regression equations. A multiple regression analysis of vNDVI and weighted abundance (WA) with measured species richness (Sv) was performed to determine how well the combined methods explain variability in species richness at the 17 study sites. A final map was made to display the areas where the three methods of estimating richness, are in most and least agreement. Cover types, richness levels, and degree of difference in richness estimates were tabulated.

Results - Vegetation
Ten land cover classes were determined:
- Water
- Snow and ice
- Rock-lichen barrens - most species poor (total 61.4%)
- Sand and gravel barrens - most species rich (total 14.5%)
- Dry acidic dwarf-shrub tundra - most species poor
- Dry non-acidic dwarf-shrub tundra - most species poor
- Low-shrub tundra, tall riparian shrubs
- Moist shrub-graminoid tundra - most species rich
- Moist and wet graminoid tundra

Rock-lichen barrens, dry acidic dwarf-shrub tundra, and dry non-acidic dwarf-shrub tundra were all species poor and were 61.4% of the vegetation. Sand and gravel barrens and moist and wet graminoid tundra were both species rich and accounted for 14.5% of the vegetation.

Results – Richness Correlations
Simple regressions between measured and estimated species richness indicated variation in NDVI and explains 65% of the variance in species richness ($r^2 = 0.653, P < 0.0001$)
The weighted abundance of vegetation types explains 34% ($r^2 = 0.340, P < 0.014$)
A multiple regression analysis indicates that together, these two variables significantly explain 79% of the variance in species richness at the 17 study sites along the Hood River (adjusted $r^2 = 0.788, P < 0.0001$)
References

