SRTM-DEM AND LANDSAT ETM+ DATA FOR MAPPING TROPICAL DRY FOREST COVER AND BIODIVERSITY ASSESSMENT IN NICARAGUA

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ABSTRACT

Tropical dry and deciduous forest comprises as much as 42% of the world's tropical forests, but has received far less attention than forest in wet tropical areas. Land use change threatens to greatly reduce the extent of dry forest that is known to contain high levels of plant and animal diversity. Forest fragmentation may further endanger arboreal mammals that play principal role in the dispersal of large seeded fruits, plant community assembly and diversity in these systems. Data on the spatial arrangement and extent of dry forest and other land cover types is greatly needed to enhance studies of forest fragmentation effects on animal populations. To address this issue, we compared two Random Forest decision tree models for land cover classification in a Nicaraguan tropical dry forest landscape with and without the use of terrain variables derived from Space Shuttle Radar and Topography Mission digital elevation data (SRTM-DEM). Landsat Enhanced Thematic Mapper (ETM+) bands and vegetation indices were the principle source of spectral variables used. Overall classification accuracy for nine land cover types improved from 82.4% to 87.4% once terrain and spectral predictor variables were combined. Error matrix comparisons showed that class accuracy was significantly greater ($z = 2.57$, p-value < 0.05) with the inclusion of terrain variables (e.g., slope, elevation and topographic wetness index) in decision tree models. Variable importance metrics indicated that a corrected Normalized Difference Vegetation Index (NDVIc) and terrain variables improved discrimination of forest successional types and wetlands in the study area. Results from this study demonstrate the capability of terrain variables to enhance land cover classification and habitat mapping useful to biodiversity assessment in tropical dry forest.

Keywords: STRM-DEM, Landsat ETM+, Random Forest classifier, tropical dry forest, land cover

RESUMO

Cobertura de floresta tropical seca e decídua abrange até 42% da floresta tropical do mundo, mas têm recebido muito menos atenção que a floresta em áreas tropicais úmidas. A mudança de uso de terra ameaça grandemente reduzir a extensão de floresta seca que é sabida conter níveis altos de diversidade de planta e animal. O fragmentação de floresta pode mais pôr em perigo mamíferos arboreais que servem papel principal na dispersão de frutas sementadas grandes, a assembléia de comunidade de planta e diversidade nestes sistemas. Os dados no arranjo espacial e extensão de floresta seca e outros tipos de cobertura de terra são grandemente precisados para aumentar estudos de efeitos de fragmentação de floresta em populações animais. Para direcionar a esta questão nós comparamos dois modelos aleatórios de árvore de decisão da floresta para classificação de cobertura de terra numa paisagem de floresta seca tropical nicaraguense com e sem o uso de variáveis de terreno derivadas do Radar da Lançadeira do Espaço e dados digitais de elevação da Missão Topografia (SRTM-DEM). As faixas do Traçador Landsat Temático Aumentado (ETM +) e índices de vegetação eram a fonte principal de variáveis espectrais usados. Exatidão total de classificação para nove tipos de cobertura de terra melhorou de 82,4% a 87,4% ao logo que variáveis de terreno e preditor espectral foram combinadas. As comparações de matriz de erro mostraram que exatidão de classe era significativamente maior ($z = 2,57$, p-valor $<0,05$) com a inclusão de variáveis de terreno (por exemplo, declive, elevação e índice topográfico de umidade) em modelos de árvore de decisão. Métricos da importância dos variáveis indicaram que um índice corrigido de Vegetação de Diferença Normalizado (NDVIc) e variáveis de terreno melhoraram discriminação de tipos de successional de floresta e terras úmidas na área de estudo. Os resultados deste estudo demonstram a capacidade de variáveis de terreno para aumentar classificação de cobertura de terra e traça de habitat útil para avaliar a biodiversidade em floresta seca tropical.

Palavras-chave: STRM-DEM, Landsat ETM+, Random Forest classifier, floresta tropical seca, cobertura do solo.

1. INTRODUCTION

Tropical dry and deciduous forest is estimated to occupy up to 42% of the world's tropical and subtropical landmass characterized as open or closed forest (Murphy and Lugo 1986). The effects of forest fragmentation on biodiversity in tropical dry environments are of critical concern in areas where human land use has substantially reduced forest cover (Defries et al. 2005). Although dry forest has been shown to be highly vulnerable to agricultural conversion and other threats (Miles et al. 2006), it has received far less attention from the scientific community than moist or wet tropical forest types (Sanchez-Azofeifa et al. 2005).

Efforts to maintain and restore dry forest may be affected by fragmentation of habitats and animal populations that are linked to ecosystem processes such as seed dispersal, plant community assembly and diversity (Holl and Kappelle 1999, Stevenson and Aldana 2008). Arboreal mammals that are important to dispersal of large seeded plants are of special concern as forest fragmentation can inhibit daily travel as well as forest connectivity important to animal movement and dependant plant populations (Chapman and Onderdonk 1998, Pacheco and Simonetti 2000). Fragmentation also increases human pressure such as hunting and capture of seed dispersing monkeys and birds for pets (Ortiz-Martínez and Rico-Gray 2007). However, threats to wildlife and plant species are mediated by species-specific sensitivity to forest disturbance and the types of matrix surrounding forest (Debinski and Holt 2000). Thus, the spatial context of remaining forest fragments and neighboring land use activities may enhance or degrade ecosystem function.

Methods to assess the spatial structure and viability of arboreal mammals and other animal populations often require ecological field studies that are combined with land cover information derived from remotely sensed data (Kerr and Ostrovsky 2003). Multispectral and multitemporal satellite images have played a primary role in characterizing land cover change and deforestation rates (Lu et al. 2004), but are fast becoming a fundamental component of conservation planning and biodiversity assessment (Sesnie et al. 2008, Stickler and Southworth 2008). However, improved cost effective and accurate methods for discriminating land cover types are needed for mapping and modeling habitat and animal population dynamics over large areas (Stickler and Southworth 2008). The need for low-cost data resources is particularly important for conservation research in developing countries where funding for mapping is often limited.

Satellite imagery and global coverage of digital elevation data from the Space Shuttle Radar and Topography Mission (SRTM-DEM) available through the Global Land Cover Facility (GLCF; http://glcf.umiacs.umd.edu/index.shtml) greatly increases access to no-cost data resources for land cover mapping. In addition, Landsat Multispectral Scanner (MSS), Thematic Mapper (TM), and Enhanced Thematic Mapper (ETM+) image archives from the >30 year program will become freely available to the public as of February 2009 (USGS 2008). Increased access to satellite and SRTM-DEM data are anticipated to improve opportunities for integrated mapping of land cover types important to conservation planning and biodiversity assessment (Sesnie el al. 2008).

For this research we combined Landsat ETM+ imagery with terrain variables derived from 90m SRTM-DEM data to map tropical dry forest fragments and agricultural land cover types in the Rivas Province of Southwestern Nicaragua. Forest and agricultural lands are concentrated across the narrow Rivas Isthmus, between Lake Nicaragua and the Pacific Coast. This area is a priority for regional conservation efforts because it contains forest remnants representative of endangered Central American lowland tropical dry forest. Forest fragments maintain western Nicaragua's last surviving populations of the black-handed spider monkey (*Ateles geoffroyi*). The spider monkey is an important seed disperser in tropical forests and is a useful indicator species of functional forest structure and connectivity (Pacheco and Simonetti 2000, Link and Di Fiore 2006). Accurate forest and agricultural cover maps are essential for assessing the viability of forest fragments to maintain threatened spider monkey populations. Land cover maps characterizing forest fragments and linkages can be used to prioritize conservation efforts such as the establishment of new protected areas and the location of restoration efforts.

In developing and testing a low-cost method for mapping tropical dry forest and agricultural land, our principle objective was to compare differences in overall and individual classification accuracy for land cover types with and without the use of SRTM-DEM derived variables. Terrain variables can potentially improve land cover classification accuracy as land use activities and infrastructure (e.g., roads) are typically linked to the biophysical environment (Sader and Joyce 1988). Therefore, we hypothesized that terrain variables would significantly enhance land cover classification and map accuracy over classifiers using spectral predictor variables alone.

Our second objective was to examine the utility of freely available data, statistical software and robust machine learning techniques to map land cover for a Nicaraguan dry forest landscape of conservation interest. We used the non-parametric Random Forest decision tree classifier (Breiman 2001) to leverage conditional relationships in the data without making distributional assumptions problematic with parametric methods (Friedl and Brodley 1997). Random Forest decision trees have also been shown to obtain superior prediction accuracy over a number of other classifiers (Gislason et al. 2006). These modes of analysis were geared toward integrating widely available multispectral and terrain variables and statistical tools for land cover classification and biodiversity assessment. Validated land cover data developed with this study is being incorporated with studies investigating forest fragmentation effects on the threatened black-handed spider monkey.

2. METHODS AND MATERIALS

2.1. STUDY AREA

The study area encompasses the narrow isthmus and Rivas Province of southwestern Nicaragua to the west of Lake Nicaragua, hereafter referred to as the "Rivas study area" (Figure 1). The Rivas study area contains the highest concentration of tropical dry forest in Nicaragua. Forest types are defined as tropical dry deciduous forest along the lowland Pacific coast to moist broadleaf forest at higher elevations (Figure 1). Elevations in the Rivas area are between sea level and 600m in the coastal mountain range. Annual precipitation averages from 1400 to 2000mm with dry periods producing <50mm of rainfall per month between December and April. Average annual air temperature is 26.7 °C. Land colonization and agricultural expansion since the 1940s has lead to a mixture of land cover types consisting of remnant coastal wetlands and mature and secondary forest re-growth amid pasture and crop lands. Conservation efforts by the non-government organization Paso Pacífico are presently aimed at maintaining and restoring forest connectivity in the Rivas study area to contribute to the development of the Mesoamerican Biological Corridor (MBC). Forest restoration activities are to replant native tree species and encourage natural regeneration in successional areas intended to sequester carbon and recover critical wildlife habitat.

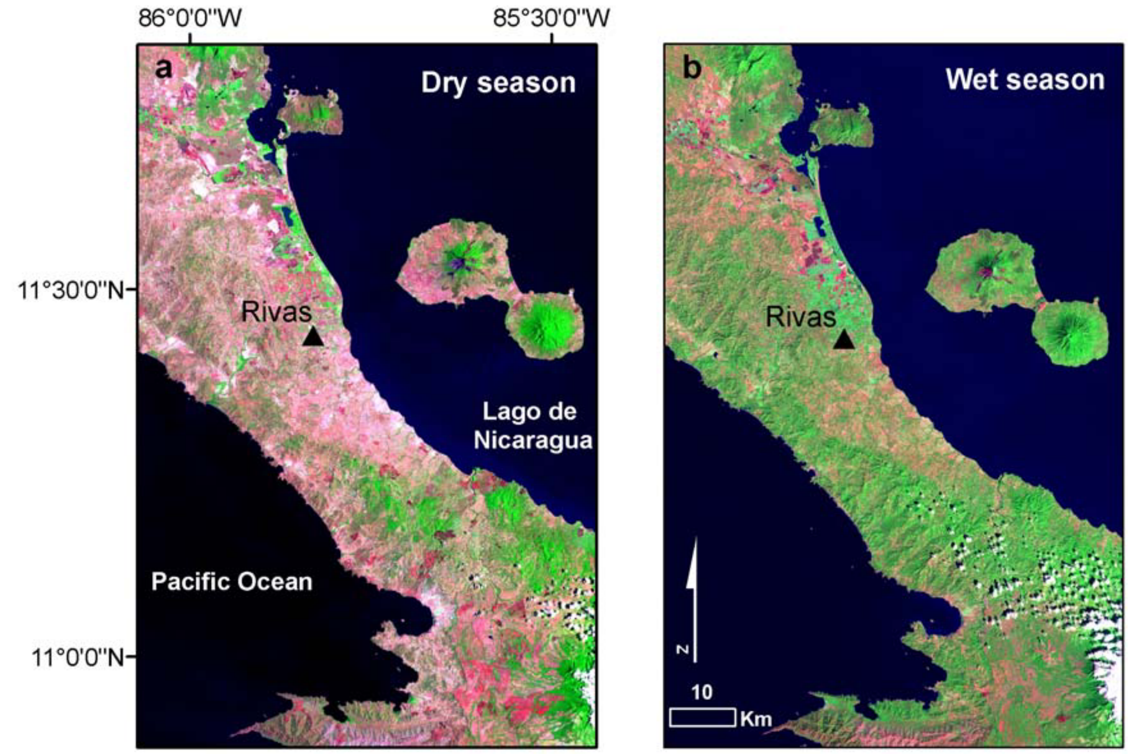

Figure 1 - Study area covering Nicaragua's southwestern isthmus with moist and tropical dry forest that are connected forest in northwestern Costa Rica (lower right). Dry (a) and wet (b) season images indicate a contrast between leaf-off and leaf-on periods for deciduous forests. At the top is a TM image from March of 1986 and bottom is a late wet season ETM+ image from January 2000.

2.2. IMAGE PROCESSING AND LAND COVER CLASSIFICATION

An orthorectified Landsat image (WRS2 path 16 row 52) with low cloud cover from January of 2000 and 90m SRTM-DEM data were downloaded from GLCF image archives. On our study area, the month of December is typically the beginning of the dry season; however variation in rainfall patterns may extend the wet season and leaf-on phase. Therefore, the January ETM+ image was contrasted with a late dry season TM image from 1986 before it was considered representative of a primarily leaf-on period (Figure 1).

A set of predictor variables derived from ETM+ spectral bands and SRTM-DEM elevation data (Table 1) were used to model and classify the land cover types described in the section below. Digital numbers (DN) for ETM+ spectral bands 1-5 and 7 (30-m resolution) were converted to reflectance values taken at the sensor using standard calibration coefficients. The panchromatic ETM+ band (15-m resolution) was also included as a predictor variable and thermal band 6 was not used. No geometric correction was applied as land features visible in the ETM+ image corresponded spatially with 2004 orthorectified aerial photographs (1-m pixels). All predictor variables were resampled to a 30m pixel resolution to match ETM+ bands. The normalized difference vegetation index (NDVI) and corrected NDVI (NDVIc) that are sensitive to Plant Area Index (PAI) and canopy closure (Nemani et al. 1993, Pocewicz et al. 2004) were used to enhance differences between late and early successional forest. Terrain variables thought to influence land use were derived from the SRTM-DEM. Topographic wetness index was derived using the Topocrop Terrain Analysis extension in ArcView 3.3 (ESRI 2002) that models soil moisture patterns (Beven and Kirkby 1979, Moore et al. 1991). Aspect was transformed to an index of solar radiation (Roberts and Cooper 1989).

Nine land cover categories were used for classification model training and mapping purposes and that could be readily interpreted from digital 2004 panchromatic aerial photographs. Because the successional status of forest remnants, canopy structure and composition were anticipated to play a role in the distribution and movement of arboreal frugivores on the study area, discriminating mature or late successional forest from young secondary forest regrowth (hereafter termed "forest" and "regrowth" respectively) was a primary focus for this study. Vegetation such as reed grass marshes, flood plain or inundated forest and mangroves were grouped into a general category termed wetlands. Other land cover categories contributing to landscape heterogeneity and possible wildlife habitat were pasture land, horticultural crops, bare soil, rock and urban areas. Cloud and shadows were masked from the classified image as a post-processing step.

A supervised land cover classification approach was used by identifying a set of training sites and pixels representing each land cover type. Training locations were interpreted from the digital aerial photographs and placed over the 2000 ETM+ image using geographically linked viewers in the ENVI v. 3.3 image processing package (ITT Industries Inc. 2006). From the training sample data, the Random Forest decision tree classifier in the R statistical package v. 2.6.2 (The R Foundation for Statistical Computing 2008) was used to map land cover from the set of spectral and terrain predictor variables. Random Forest decision tree models were derived from multiple model runs (n = 2000 classification trees) with bootstrap training samples leaving a portion of the data aside for accuracy assessment. Each tree was independently derived and tested for accuracy by running data withheld from the training sample (about 1/3rd) down the respective tree. Each tree contributed a unit vote for the most popular class (e.g., a land cover category) and error was aggregated from the number of trees requested (Breiman 2001).

Table 1 - Predictor variables used with Random Forest classification trees for land cover classification.

Landsat ETM+	**Units**	**Spatial res. (m)**	**Equation**
b1	0.45-0.51µm	30	_
b2	0.52-0.60 µm	30	_
b3	0.63-0.69 µm	30	_
b4	0.75-0.90 µm	30	_
b5	1.55-1.75 µm	30	_
b7	2.08-2.35 µm	30	_
pan	0.52-0.90 µm	15	_
NDVI	-1- +1	30	b4-b3/b4+b3
NDVIc	-1- +1	30	b4-b3/b4+b3*[1-(b5-$b5_{min}$)/($b5_{max}$-$b5_{min}$)][1]
SRTM-DEM			
Elevation (el)	m	90	_
Slope	%	90	_
Topographic wetness index (twi)	0-16	90	_
Transformed aspect (trasp)	0-1	90	$(1-\cos((aspect-30)*\pi/180))/2$

[1]Band 5 maximum and minimum values were taken from an open pasture and closed forest canopy on level terrain.

2.3. DATA ANALYSIS

Classification accuracy was evaluated for each land cover type from two separate classifiers with and without the use of SRTM-DEM derived terrain predictor variables for comparison. Error matrices for each classifier were used to compare overall percent accuracy and percent accuracy within each land cover category (Congalton and Green 1999). The relationship between land cover, terrain variables and classification accuracy was tested by comparing correctly classified pixels left out of the bootstrap training sample. Therefore, correctly classified pixels along the main diagonal of the error matrix were treated as a discrete random variable and compared using a Wilcoxon signed rank test (test statistic = Z, á = 0.05). We hypothesized that the inclusion of terrain variables would lead to a significantly greater ($\mu > 0$, $P < 0.05$) number of correctly classified validation pixels. Relationships in the data such as the influence of topography and soil moisture on land use were anticipated to improve accuracy by accounting for these conditions in the set of predictor variables.

The importance of predictor variables to land cover classification accuracy was also estimated using Random Forest trees and permuting each predictor out of multiple decision tree model runs (2000 trees). The mean decrease in accuracy from class sample data left out of bootstrap training samples was used as a measure of variable importance (Breiman 2001). Further technical details for machine learning classifiers and spatial modeling procedures used with this study can be obtained from randomForest and yaImpute documentation with the R statistics package (http://cran.r-project.org/).

3. RESULTS

Error matrices from the two separate Random Forest classifiers resulted in greater land cover classification accuracy when terrain variables were included (Table 2a, b). Overall class accuracy increased from 82.4% to 87.4% with the addition of terrain variables. Terrain variables also contributed to a notable reduction in misclassification error rates for individual land cover categories with the exception of horticulture crops (Table 2a, b). Particularly important to this study was a 3% to 6% reduction in misclassification error for the two forest and regrowth categories in addition to a 20% reduction for the wetlands category.

Terrain data significantly increased ($Z = 2.57$, $P < 0.05$) the number of correctly classified validation pixels based on error matrix comparisons (main diagonal) from the two separate classifiers. Map accuracy was e" 80% for land cover categories using all thirteen ETM+ and STRM-DEM variable, which we considered exceptional for characterizing landscape heterogeneity and forest fragmentation patterns in the study area.

Both spectral and terrain variables were important in the accurate classification of forest and wetlands types (Figure 2). Overall, NDVI, NDVIc, ETM+ band 7 (mid-infrared) were the most important variables. However, NDVIc and percent slope were among the most important variables for accurately classifying both regrowth and wetlands categories. NDVIc was also highly important to accurately discriminating forest from other land cover types (Figure 2). The separability of forest and regrowth areas was greatly improved with NDVIc when compared to NDVI (Figure 3a, b). Recalibrating NDVI for open and closed forest canopy conditions using the mid-infrared ETM+ band 5 dramatically improved the sensitivity to forest structural differences between the two successional classes (Figure 3b).

Mapped forest and regrowth areas corresponded with remaining forest occurring on steep or uneven terrain less suitable for agriculture (Figure 4). More extensive forest and regrowth areas were primarily observed in mountainous terrain (Figures 4, 5). Conversely, areas of low topography along the west edge of Lake Nicaragua were largely dominated by agricultural lands with the exception of coastal wetlands and forest retained along riparian corridors (Figure 5). Indeed, the relationship between topography, land use and spatial location of land cover types helped to explain a statistically significant increase in overall classification accuracy from comparisons above.

Variation in annual and seasonal rainfall in the study area was also important to accurately estimating the remaining extent of tropical dry forest and regrowth in the study area. Visual comparisons of images from leaf-off and leaf-on periods indicate that the extent of forest categories would likely be severely underestimated from dry season imagery (Figure 4). Images obtained during the late dry season (March) suggested that extensive areas are devoid of green vegetation and forest cover in the Rivas study area (Figure 4). Despite the onset of a dry season as early as December, the January ETM+ image and land cover classification showed that forest and regrowth areas were visually consistent forested areas in high spatial resolution aerial imagery (Figure 4). Inter-annual differences and extended periods of rainfall in some years are important for obtaining low cloud cover images during leaf-on periods for accurate characterization of tropical dry forest cover.

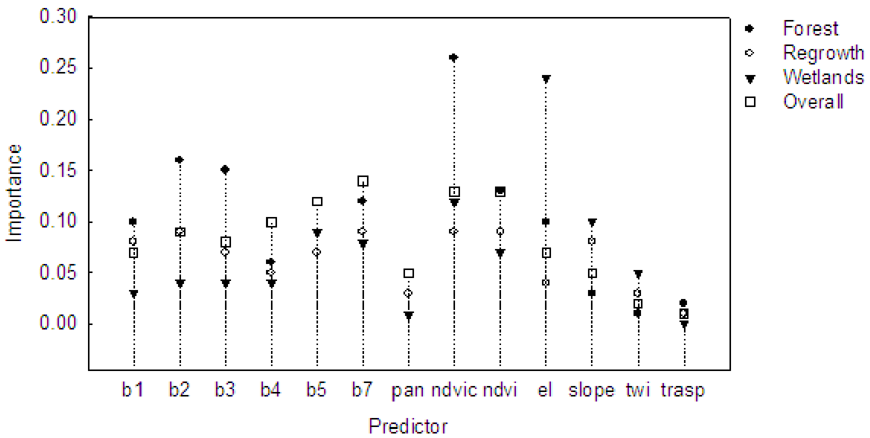

Figure 2 - Random Forest predictor variable importance plot for classifying forest, regrowth and wetlands land cover types in addition to the overall mean decrease in classification accuracy (importance) attributed to each predictor variable.

Table 2 - Error matrices generated from the Random Forest classifier using a) spectral predictor variables only and b) spectral and terrain predictor variables. Error is estimated from predicted class samples from data left out of the bootstrap training sample.

a)

Predicted \ Ref.	crops	forest	pasture	regrowth	rock	soil	urban	water	wetlands	Error
crops	**65**	1	3	1	0	0	0	0	6	14.5%
forest	0	**110**	0	17	0	0	0	1	3	16.0%
pasture	1	0	**85**	6	1	7	0	0	1	15.8%
regrowth	1	24	4	**83**	0	0	0	0	1	26.5%
rock	0	0	0	2	**25**	2	1	1	0	19.4%
soil	0	0	3	0	2	**50**	6	0	0	18.0%
urban	0	0	2	0	0	11	**32**	0	0	28.9%
water	0	0	0	0	3	0	0	**113**	0	2.6%
wetlands	7	3	1	4	0	0	0	0	**25**	37.5%

b)

Predicted \ Ref.	crops	forest	pasture	regrowth	rock	soil	urban	water	wetlands	Error
crops	**65**	2	5	1	0	0	0	0	3	14.5%
forest	0	**114**	0	15	0	0	0	1	1	13.0%
pasture	2	0	**89**	5	1	4	0	0	0	11.9%
regrowth	1	19	3	**90**	0	0	0	0	0	20.4%
rock	0	0	0	1	**28**	0	0	1	1	9.7%
soil	0	0	3	0	1	**54**	3	0	0	11.5%
urban	0	0	2	0	0	7	**36**	0	0	20.0%
water	0	0	0	0	1	0	0	**115**	0	0.9%
wetlands	5	0	0	2	0	0	0	0	**33**	17.5%

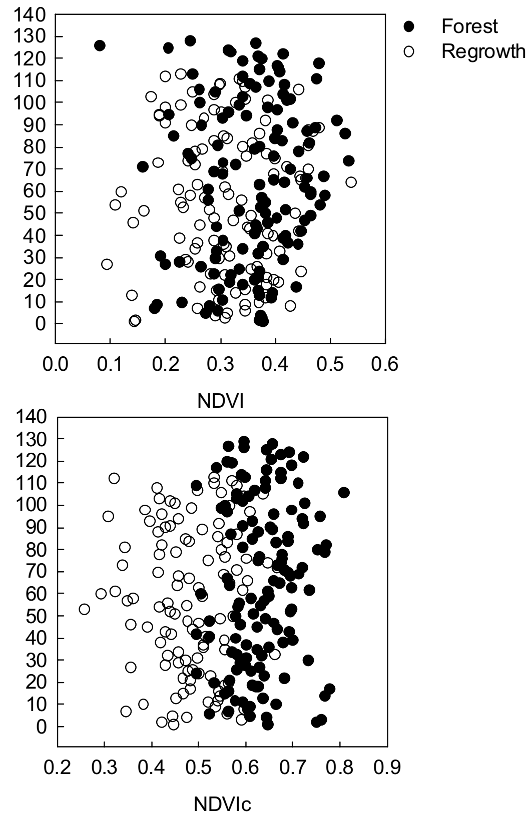

Figure 3 - Separability comparison of forest and regrowth areas attributed by a) NDVI and b) NDVIc values.

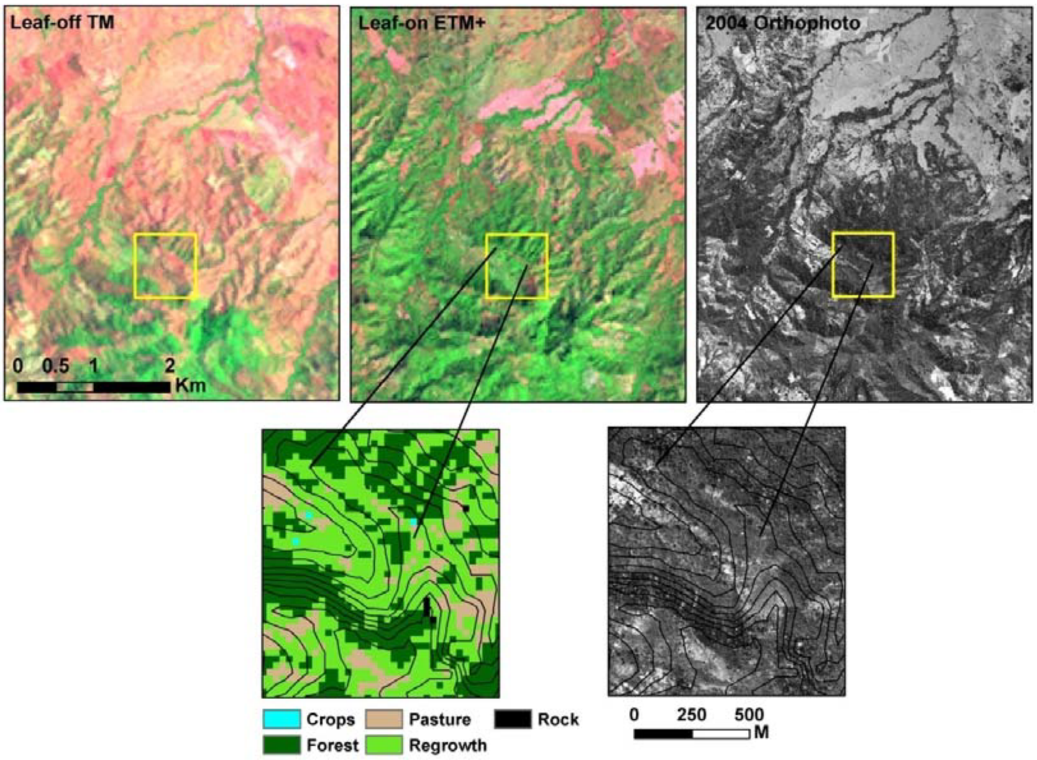

Figure 4 - Forest and regrowth areas within the Rivas study area viewed from leaf-off and leaf-on Landsat images (top). Pasture, forest and regrowth areas mapped from SRTM-DEM derived terrain variables and the leaf-on ETM+ image correspond well with 2004 panchromatic orthophotographs from the study area (bottom).

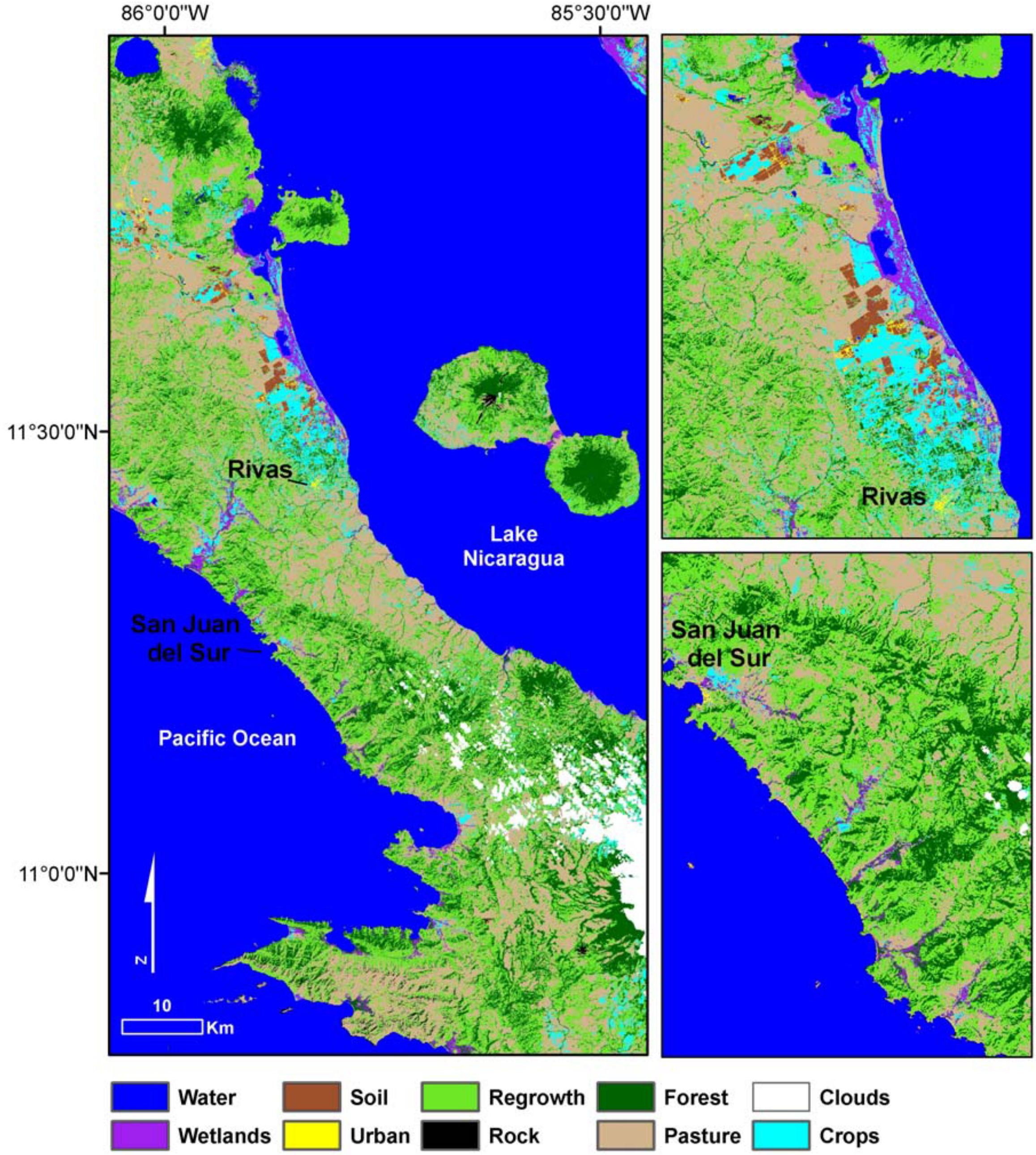

Figure 5 - Land cover map of the Rivas study area from Random Forest classification trees combining Landsat ETM+ spectral variables and SRTM-DEM derived terrain predictor variables.

4. DISCUSSION AND CONCLUSIONS

Dry forest and regrowth areas in addition to other land cover types appear to be spatially structured, in part, by the biophysical environment and land use activities in the Rivas study area. Based on our comparisons, terrain variables can improve land cover classification models that attempt to discriminate tropical dry forest and early successional areas from other land cover types. Very little forest and successional vegetation remains in areas of low topography and elevation in the Rivas study area, thus improving the accuracy of land cover categories mapped with terrain data. Accurate discrimination of wetlands was also improved with the addition of topographic and elevation data that are linked to hydrologic conditions on these sites and surrounding land use.

Gain in classification accuracy for the Rivas land cover map are in spite of lower spatial resolution (e.g., 90m vs. 30m SRTM-DEM) and vertical errors (~16-m mean vertical offset) known to occur with SRTM elevation values for sub-tropical dry (Florida) and rain forest types (Gillespie et al. 2006, Hofton et al. 2006). Vertical error and spatial resolution undoubtedly impact models of terrain features, local hill-slope variation and surface hydrology important for land cover classification (Sesnie et al. 2008). Nevertheless, the effects of vegetation phenology on synthetic aperture radar data in tropical dry forest remain unclear. The acquisition date (Feburary 11 of 2000) of SRTM data corresponds with a partial leaf-off period in the Rivas study area. The C-band wave-lengths (5.8cm) used to create STRM elevation data interact with canopy foliage and branches and it is not currently known how leaf-off periods affect elevation values derived from radar data at these latitudes (but see Gillespie et al. 2006). It is, however, likely that broad-scale land cover categories used with this study are less affected by vertical error in SRTM elevation data. Mapping of forest composition and more detailed land cover types would likely require improved elevation data to more accurately model local topography and hydrologic function.

We found that NDVI and NDVIc were also important to the classification results obtained (Figure 3). A number of studies report the utility of spectral vegetation indices for discriminating successional classes in tropical dry forest (Arroyo-Mora et al. 2005, Freely et al. 2005, Kalacska et al. 2005). NDVIc which incorporates maximum and minimum values from the mid-infrared spectral region (ETM+ band 5) has shown increased sensitivity and a positive relationship with PAI in temperate coniferous forests (Nemani et al. 1993, Pocewicz et al. 2004). In our study, NDVIc was highly important to discriminating forest from other land cover types, principally early successional forest regrowth. Greater NDVIc values in late successional dry forest are potentially due to greater canopy closure and PAI than in early successional stages. However, field measurements by Kalascka et al. (2005) found that PAI was generally lower in later successional stages for two dry forest sites in Costa Rica. High understory development of woody plants on early successional sites may explain differences observed in Costa Rican forests. Kalascka et al. (2005) suggested that the interdependence of PAI, canopy openness and local climate variation was important to quantifying differences among dry forest successional stages. No field measurements were taken to examine these relationships in the present study and further detailed field studies to determine relationships between PAI, forest structure and spectral vegetation indices are clearly warranted for comparison among sites (Kalascka et al. 2005).

The land cover classification methods and data resources explored with the Rivas study area are applicable to other tropical dry forest areas and ecosystems. Random Forest decision trees provide a robust method to integrate predictor variables for land cover classification, assess variable importance, and improve classification accuracy (Breiman 2001). These methods dramatically improve the operability of remotely sensed data for conservation and biodiversity assessment in a cost-effective manner. Limitations of the approach used are the temporal separation of the various input data obtained and unavailability of ground reference data. However, the collection of ground data are unlikely to confirm classification accuracy of land cover types derived from the available 2000 ETM+ image. Rapid land use and land cover change in the study area suggests that bootstrapped error estimates from Random Forest trees provide a practical alternative to the use of ground reference data that is expensive to collect and temporally infeasible.

The linkage between landscape structure, animal populations and ecological function are as yet unclear in tropical dry forest ecosystems. Importantly, land cover data generated for the Rivas study area increase opportunities to investigate the effects of forest fragmentation on spider monkey and other wildlife populations and potential outcomes of ongoing forest restoration activities in the study area. Future efforts that characterize land cover applying the classification techniques validated with this study, as well as up-to-date multispectral images, will contribute to improved knowledge of land cover dynamics and changes as they occur in this and other tropical dry forest landscapes.

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5. REFERENCES

Arroyo-Mora, J. P., G.A. Sánchez-Azofeifa, M.E.R. Kalacska, and others, 2005. Secondary forest detection in a Neotropical dry forest using Landsat 7 ETM+ and IKONOS imagery. Biotropica , v. 37, no. 4, p. 497-507.

Beven, K. J., and M.J. Kirkby, 1979. A physically based variable contributing area model of basin hydrology. Hydrological Sciences Bulletin, v. 24, p. 43-69.

Breiman, L., 2001, Random forests: Machine Learning, v. 45, p. 5-32.

Chapman C.A. and Onderdonk D.A. 1998. Forests without primates: Primate/plant codependency. American Journal of Primatology, v. 45, p. 127-141.

Congalton, R. G., and K. Green, 1999. Assessning the accuracy of remotely sensed data: principles and practices: Boca Raton, FL, CRC/Lewis Publishers.

Debinski, D. M., and R.D. Holt, 2000. A survey and overview of habitat fragmentation experiments. Conservation Biology, v. 14, p. 342-355.

Defries, R. A., A. Hansen, A.C. Newton, and others, 2005. Increased isolation of protected areas in tropical forest over the past twenty years. Ecological Applications, v. 15, p. 19-26.

Freely, K. J. , 2005, The utility of spectral indices from Landsat ETM+ for measuring structure and composition of tropical dry forest. Biotropica, v. 37, p. 508-519.

Friedl, M. A. , and C.E. Brodley, 1997. Decision tree classification of land cover from remotely sensed data. Remote Sensing of Environment , v. 61, p. 399-409.

Gillespie, T. W., B.R. Zutta, M.K. Early, and others, 2006. Predicting and quantifying the structure of tropical dry forest in South Florida and Neotropics using spaceborne imagery. Global Ecology and Biogeography, v. 15, p. 225-236.

Gislason, P. O., J.A. Benediktsson, and J.R. Sveinsson, 2006. Random forests for land cover classification. Pattern Recognition Letters, v. 27, p. 294-300.

Hofton, M., R. Dubayah, J.B. Blair, and others, 2006. Validation of SRTM elevations over vegetated and non-vegetated terrain using medium footprint Lidar. Photogrammetric Engineering and Remote Sensing, v. 72, p. 279-285

Holl, K. D., and M. Kappelle, 1999. Tropical forest recovery and restoration. Trends in Ecology & Evolution, v. 14, no. 10, p. 378-379.

Kalacska, M. E. R., A.G. Sánchez-Azofeifa, J.C. Calvo-Alvarado, and others, 2005. Effects of season and successional stage on Leaf Area Index and spectral vegetation indices in three Mesoamerican tropical dry forests. Biotropica, v. 37, no. 4, p. 486-496.

Kerr, J. T., and M. Ostovsky, 2003. From space to species: ecological applications for remote sensing. Trends in Ecology and Evolution, v. 18, no. 6, p. 299-305.

Link, A., Di Fiore A., 2006. Seed dispersal by spider monkeys and its importance in the maintenance of neotropical rain-forest diversity. Journal of Tropical Ecology, v. 22, p.235-246.

Lu, W., P. Mausel, E. Brondízio, and others, 2004. Change detection techniques. International Journal of Remote Sensing, v. 25, p. 2365-2407.

Miles, L., A.C. Newton, R.S. Defries, and others, 2006. A global overview of the conservation status of tropical dry forest. Journal of Biogeography, v. 33, p. 491-505.

Moore, T. D. , R.B. Grayson, and A.R. Ladson, 1991. Digital terrain modeling - A review of hydrological, geomorphological, and biological applications. Hydrological Processes, v. 5, p. 3-30.

Murphy, P. G., and A.E. Lugo, 1986. Ecology of tropical dry forest. Annual Review of Ecology and Systematics, v. 17, p. 67-88

Nemani, R., L. Pierce, S. Running, and others, 1993. Forest ecosystem processes at the watershed scale: sensitivity to remotely-sensed Leaf Area Index estimates. International Journal of Remote Sensing, v. 14, no. 13, p. 2519-2534.

Ortiz-Martínez, T., and V. Rico-Gray, 2007. Spider monkeys (*Ateles geoffroyi vellerousus*) in a tropical deciduous forest Techauntepec, Oaxaca, Mexico. The Southwestern Naturalist, v. 52, no. 3, p. 393-399.

Pocewicz, A. L., P. Gessler, and A.P. Robinson, 2004. The relationship between effective plant area index and Landsat spectral response across elevation, solar insolation, and spatial scales in a northern Idaho forest: Canadian Journal of Forest Resources, v. 34, p. 465-480.

Pacheco L.F., Simonetti J.A. 2000. Genetic structure of a mimosoid tree deprived of its seed disperser, the spider monkey. Conservation Biology, v. 14, p.1766-1775.

Roberts, D. W., and S.V. Cooper, 1989. Concepts and techniques of vegetation mapping. In: Land classifications based on vegetation: applications for resource management: USDA Forest Service General Technical Report INT-257, Ogden, UT, p. 90-96.

Sader, S. A., and A.T. Joyce, 1988. Deforestation rates and trends in Costa Rica, 1940 to 1983. Biotropica, v. 20, no. 1, p. 11-19.

Sesnie, S. E., P.E. Gessler, B. Finegan, and others, 2008. Integrating Landsat TM and SRTM-DEM derived variables with decision trees for habitat classification and change detection in complex neotropical environments: Remote Sensing of Environment, v. 112, p. 2145-2159.

Stevenson, P. R., and A.M. Aldana, 2008, Potential effects of ateline extinction and forest fragmentation on plant diversity and composition in the Western Orinoco Basin, Colombia. International Journal of Primatology, v. 29, p. 365-377.

Stickler, C. M., and J. Southworth, 2008. Application of multi-scale spatial and spectral analysis for predicting primate occurrence and habitat associations in Kibale National Park, Uganda. Remote Sensing of Environment, v. 112, p. 2170-2186.

Sánchez-Azofeifa, G. A., M. Quesada, J.P. Rodríguez, and others, 2005. Research priorities for Neotropical dry forests. Biotropica, v. 37, no. 4, p. 477-485.

USGS, 2008. Imagery for everyone: timeline set to release entire USGS Landsat archive at no charge. Technical Announcement, p. 1.