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Assessing the Conservation Status of Neotropical Dry Forests using Geographical Information Systems and Optical Remote Sensing

by

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ABSTRACT

This thesis is composed of five chapters assessing the following specific goals: 1) To estimate the extent and geographic distribution of the neotropical dry forest. 2) To evaluate the potential use of satellite-detected fires as deforestation predictors in tropical dry forest and 3) To evaluate the potential of remote sensing techniques to detect edge effects in tropical dry forest. Preliminarily, in chapter two, I present a literature review of the techniques and concepts behind remote sensing of biodiversity. Here, I stress out the necessity of integrated assessments using multiple spatial and spectral resolution sensors over a wide array of ecosystems in order to find relevant ecosystem properties that would be sensitive to taxonomic and functional biodiversity. Chapter three describes a regional scale mapping effort of the extent and geographical distribution of tropical dry forests. Our results indicate that the total extent of tropical dry forest in the Americas is 519,597 Km^2 with only 4.5 % being under protected areas. Results are also presented by subregions and countries. In Chapter four, we show correlations patterns between the number of MODIS Active Fires and forest cover change in four tropical dry forest landscapes in Latin America. At the Santa Cruz site (Bolivia), correlations were strong and significant while at Chamela Site (Mexico) and the Mata Seca site (Brazil) correlations were moderate but significant as well. Chapter five addresses the magnitude of disturbances near the edges of dry forest fragments (edge effects). Results in gap fraction and Fraction of Intercepted Photosynthetically Active Radiation (FiPAR) show that edge influence at tropical dry forests can extend to at least 300-m. Finally, Chapter Six shows the correlation between FiPAR changes at the forest edge and spectral vegetation indices (SVIs) computed from the hyperspectral and multiangular satellite imagery. The work contained in these five chapters address issues that are critical to the advancement of tropical dry forest monitoring. These studies contribute to the current scientific literature on the use and application of optical remote sensing tools, not only applicable in tropical dry forests, but for tropical forest conservation at the continental, regional and local level.

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CHAPTER 1 – Introduction

Unprecedented anthropogenic changes in the biosphere are a main topic for discussion in the global political agenda (UNEP, 2008). Global targets to achieve sustainable development have been set and adopted by the majority of countries around the world explicitly recognizing the value of biodiversity and the importance of rethinking current human development and exploitation of natural resources (Balmford et al. 2002, UNEP. 2008). The necessity to quantify changes in the past, identify current trends and predict future scenarios has never been greater and our ability to do so, will determine our capacity to create and implement solutions to prevent further deterioration of the environment and at the same time, balance the needs between economic development and environmental protection. In this context, remote sensing and geographic information systems (GIS) technology emerge as cutting-edge tools capable of providing the scientific community with essential indicators of the past, present and future state of ecosystems around the world (Turner et al. 2003; Gillespie et al. 2008). Spectral information of terrestrial features acquired from sensors orbiting the earth allows discrimination and quantification of ecosystem properties and functions in space and time (Ustin et al.2004). The analysis and integration of this information with other spatially-explicit databases using Geographic Information systems (GIS) have also been important to fill gaps of information and understand local to global trends in environmental change. In fact, earth observation data is now needed to fulfill the requirements of a host of international treaties and conventions (United Nations, 2002; Balmford et al. 2002).

Remote sensing applications have been especially important to understand the current tropical deforestation crisis (Achard et al. 2003; Skole & Tucker, 2003). As tropical deforestation is considered a major environmental problem, many studies using both coarse and high resolution optical remotely sensed data have attempted to measure the extent and magnitude of the phenomenon and model the drivers of change (Mayaux et al. 2005). Remote sensing not only allows to produce up-to-date estimates of forest cover and cover change, but has also been widely studied to provide spectral indicators of forest ecosystem productivity, species composition, forest structure and phenology (Turner et al., 2003). However, in order to provide sound ecological and functional information derived from remote sensing, the integration between a strong knowledge of ecological processes and patterns and imaging spectrometry is essential. This integration is important as a validation exercise, but also as a source of new analytical techniques that can maximize the ecological value of remotely sensed products and its utility for environmental conservation.

In this context, my research begins with a literature review on the current state and future prospects of biodiversity research using remote sensing and then focuses on the application of remote-sensing techniques to address specific gaps in tropical forest conservation. The main goal of this doctoral dissertation is to improve the scientific knowledge of land cover/land use dynamics in tropical dry forests ecosystems across the Americas (also known as Neotropical Dry Forests) using GIS and remote sensing tools. This ecosystem is considered one of the most threatened ecosystem in the tropics and has been highlighted as one of most important global change frontiers (Sanchez-Azofeifa et al. 2005). I also expect that this dissertation will contribute towards the facilitation of current remote sensing tools for biodiversity conservation at the continental, regional and local level. This assessment involves exploring and evaluating three scientific hypothesis:

a) The integration of Geographic Information Systems (GIS), machine learning/decision tree classifiers and accuracy assessment techniques, plus a strong knowledge of the ecosystem temporal and spatial properties, will improve the recognition of spectral values that accurately represent tropical dry forests from coarse-resolution imagery (500-m pixel resolution) and provide a better estimate of its extent and geographical distribution at the continental level.
b) Tropical dry forest loss is higher where the use of fire for land clearing purposes is more frequent. Thus, the detection of tropical dry forest loss hotspots can be done via the use of density grids of satellite-detected fire occurrence localities.
c) In a tropical dry forest fragment, the exposure of its perimeter to different microclimate conditions in the adjacent non-forest environment produces changes on the forest structure and species composition that can reach from several tenths to hundreds of meters from the edge to the interior of the forest. Because these effects affect the soil exposure and vegetation cover, they should translate to spectral changes that can be modeled from multispectral and hyperspectral satellite imagery.

Specific goals:

In the context of the goals and objectives mentioned above, the specific goals of my doctoral dissertation are:

1) To estimate the extent and geographic distribution of the neotropical dry forest via the use of pattern recognition techniques that are based on artificial inteligence classifiers applied to coarse resolution satellite imagery.
2) To evaluate the potential use of satellite-detected fires as deforestation predictors in tropical dry forest ecosystems.
3) To evaluate the potential of optical remote sensing techniques to detect edge-to-core physical disturbances in tropical dry forest fragments through the use of spectral vegetation indices.

CHAPTER SYNOPSIS

Chapter two, *Integrating Remote Sensing and Biodiversity research*, gives a comprehensive literature review of the concept of remote sensing in the light of the conceptual framework of biodiversity. Previous published reviews on the subject such as Nagendra (2001); Kerr & Ostrovsky (2003), Turner et al. (2003), Gillespie et al. (2008) have compiled important information on the several different applications of remote sensing for assessing ecological properties of ecosystems, but often fall short in describing how remote sensing techniques assess biological diversity as conceptualized and understood by ecologists and biogeographers. This chapter starts by describing the concept of biodiversity, the components of biodiversity and the determinants of biodiversity, and follows with a description how these have been assessed by remote sensing in the recent years.

Following this introductory chapter, I present four chapters aimed to satisfy the goals and objectives of the doctoral dissertation. Along these, the tropical dry forest is spatially conceptualized differently according to the geographical level on which is being assessed. It is important to clarify our interpretations of the spatial concept of forest at these three levels in order to minimize conceptual ambiguity (Bennet, 2001).

In chapter three, we assess tropical dry forests at the regional level. Here, dry forests are a seen as a group of compositionally and phylogenetically different regions of deciduous forest vegetation distributed across America, which are composed by large and small patches. In chapter four, dry forests are studied at the landscape level. In this chapter, dry forests are represented by a group of patches of dry forest vegetation, which are embedded in a human-dominated landscape and pressured by local human socioeconomic activities. In chapter five and six, dry forests are investigated at the patch level. At this level, the dry forest is represented by a single patch of deciduous forest vegetation composed by a forest edge area and a forest core area. The edge area of the forest is the perimeter of the patch which is physically and biologically affected by exposition to non-forest environmental conditions. The core of the fragment is represented by the dry forest areas that remain undisturbed by edge influence. A description of the these four chapters follows.

Chapter three, *Extent and Conservation of tropical dry forests in the Americas*, describes a regional scale mapping effort using coarse-scale imagery (Moderate Resolution Imaging Spectroradiometer – MODIS- 500-m) of the extent and geographical distribution of tropical dry forests. This chapter introduces several innovations to previous assessments on the same ecosystem such as imagery selection based on latitudinal gradients of phenology, decision tree/machine learning image classification techniques and validation efforts. This work reports important basic information on the degree of ecosystem conservation and protection by country and at sub-continental and continental levels and has already been published in the journal *Biological Conservation* (Portillo & Sanchez, 2010).

Chapter four, *MODIS Active fires and deforestation in tropical dry forest landscapes*, shows results from using one of the most recent and promising tools for highlighting tropical forest cover change which is the MODIS Active Fires product. This product is derived from the processing of thermal bands from MODIS sensor on board the Terra & Aqua satellites (Giglio et al. 2003). Apart from traditional change detection techniques, the use of remotely-sensed fires as a tool to identify deforestation fronts is very promising but it has only been suggested for humid tropical forests. Previous studies have reported difficulties in finding significant relationships between fire and deforestation in tropical dry forest. In this study, we show different correlations patterns between the number of MODIS Active Fires and forest cover change in four tropical dry forest landscapes in Latin America. Based on the results, I make further suggestions for establishing a fire-monitoring system to detect deforestation fronts in a tropical dry forest landscape.

Chapter five, *Edge influence on canopy openness and understory microclimate in two Neotropical dry forest fragments*, addresses one of the most characteristic features of fragmented tropical forests which is the increase in disturbance near the edges of the fragment or what is known as “edge effects” (also referred as edge influence). Studies regarding edge effects in tropical dry forests are few (Toledo-Aceves & Garcia-Olivo, 2008; Zelikova & Breed 2008). Most of the studies have taken place in tropical rainforests and information about the resilience and regeneration capacity of tropical dry forest to these disturbances is unknown. Here, we present, for the first time, results from eight edge-to-interior transects surveyed in two tropical dry forest fragments located in Venezuela and Brazil. The specific objective of this study was to evaluate the magnitude and distance of edge influence on the amount of visible light penetrating the canopy and the magnitude and distance of edge influence on understory microclimate conditions.

Finally, Chapter Six, *Remote sensing of edge effects in dry forest fragments using CHRIS/Proba Imagery*, is a continuation of chapter five and shows an assessment of changes in the Fraction of intercepted Photosynthetically Active Radiation (FiPAR) across four edge-to-interior transects in tropical dry forests fragments and its correlation to spectral vegetation indices (SVIs) computed from the hyperspectral and multi-angular CHRIS sensor on board of the Proba platform (Shaker et al. 2008). Our results show the potential of spectral vegetation indices for identifying and quantifying edge effects in tropical forests which can improve current efforts in modeling forest disturbance in fragmented landscapes.

SUMMARY OF LIMITATIONS TO RESEARCH PROJECTS

Several aspects of the thesis research were challenged by data availability, instrumental/sensor limitations, and logistical aspects of field sampling. For example, in chapter three, a survey of MODIS Imagery for three consecutive years (2003, 2004, 2005) at the peak of the dry and the wet season was necessary in order to find cloud free images. These specific type of images were difficult to find, and further image processing, cloud masking and mosaicking was necessary. For North America sites, the dry forest cover classification proved to give better results using daily surface reflectance imagery while for South America and the Caribbean islands the best classification was found using 8-day averaged surface reflectance imagery. Although validation and visual inspection secured the delivery of an accurate map (82% Overall accuracy), these differences may account for spatial variability of the accuracy of the map that is not quantified in the work. Other limitations at this stage and potential sources of error, were overcome or minimized with image processing, cloud masking, and extensive visual inspection, manual recoding and validation of the areas classified as forest in the image which are explained along several sections in the chapter.

Chapter four was dependant on availability of imagery for the time-series dates. This limited the locations studied and the time frame of the deforestation analysis for each site. Ideally, I would have identified deforestation events that occurred strictly between the initial and final months of the 2002-2004 period, however, in most of the cases cloud-free satellite imagery was not available for these dates and acquisition of imagery for the years 2001 and 2005 was necessary in order to include the total accumulation of deforestation events occurred during the 2001-2004 period. Furthermore, images available for the Machango site (Venezuela) had significant missing data from a Landsat ETM+ Scan Line Corrector (SLC) error which might have misrepresented true land cover trends for this site. Moreover, although the CHRIS/Proba imagery used in chapter six was on-demand, that alone did not ensure that images were cloud free and that proper coverage of all field sites was met. Images at different angles of observation often covered different parts of the sites which limited the amount of field transects that could be compared to spectral vegetation indices. Ideally, both field collection and image collection would be taken during the same time period. However, the collection dates for images and the field sampling were apart by 6 months at the Venezuela site and 1 month for the Brasil site.

In chapter five, the logistics in the field, both in Venezuela and Brasil, made selection of sites a difficult task. In Hato Piñero site, located in the Venezuelan Llanos, the onset of the wet season brings flooding events that can reach up to 2 m within some areas of the forest fragment studied. The selection of sites was therefore made in areas that were not subject to flooding and transects surveyed were confined to a smaller area of the fragment. Also, lack of self transportation made field sampling dependent on internal transport routes and schedules, which were not always practical or adapted to field sampling requirements. In the other hand, at the Mata Seca site, mature tropical dry forests were not widely distributed. The area is mainly covered by secondary dry forest, with late stage forest mainly restricted to a section of the natural park. This limited the availability and selection of forest edges to be surveyed.

FINAL COMMENTS

The five chapters of this thesis research are focused in deriving remote sensing and GIS tools for monitoring environmental change in tropical dry forests. The three main subjects of the thesis: extent and geographical distribution of the ecosystem, the evaluation of MODIS active fires as deforestation predictors, and the potential of remote sensing in modeling edge effects address important information gaps regarding tropical dry forests in the scientific literature.

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LITERATURE CITED

Achard, F., H. D. Eva, H.-J. Stibig, P. Mayaux, J. Gallergo, T. Richards, and J.-P. Malingreau. 2002. Determination of deforestation rates of the world's humid tropical forests. Science 297 (5583):999-1002

Balmford, A., L. Bennun, B. Brink, D. Cooper, I.M. Côté, P. Crane, A. Dobson, N. Dudley, I. Dutton, R.E. Green, R. Gregory, J. Harrison, E.T. Kennedy, C. Kremen, N. Leader-Williams, T. Lovejoy, G. Mace, R. May, P. Mayaux, J. Phillips, K. Redford, T.H. Ricketts, J.P. Rodriguez, M. Sanjayan, P. Schei, A. Van Jaarsveld, & B. A. Walther. 2005. The Convention on Biological Diversity's 2010 target. Science 307: 212-213.

Bennet, B. (2001) What is a Forest? On the vagueness of certain geographic concepts. Topoi 20:189-201.

Gillespie, T.W., G.M. Foody, D. Rocchini, A.P. Giorgi, and S. Saatchi. 2008. Measuring and modelling biodiversity from space. Progress in Physical Geography 32 (2): 203-221.

Giglio, L., J. Descloitres, C. O. Justice, and Y. J. Kaufman. 2003. An enhanced contextual fire detection algorithm for MODIS. Remote Sensing of Environment 87:273–282.

Kerr, J.T.; M. Ostrovsky. 2003. From space to species: ecological applications for remote sensing. Trends in Ecology & Evolution 18(6): 299-305.

Mayaux, P.; P. Holmgren; F. Achard; H. Eva; H-J Stibig; A. Branthomme. 2005. Tropical forest cover change in the 1990's and options for future monitoring. Phil.Trans.R. Soc. B. 360: 373-384.

Nagendra, H. 2001. Using remote sensing to assess biodiversity. International Journal of Remote Sensing 22(12): 2377-2400.

Portillo C. & Sanchez A. (2010) Extent and Conservation of tropical dry forests in the Americas. Biological Conservation 143:144-155.

Sánchez-Azofeifa, G.A., M. Quesada, J.P. Rodríguez,, J.M. Nassar, K.E. Stoner, A. Castillo, T. Garvin, E.L. Zent, J.C. Calvo-Alvarado, M. Kalacska, L. Fajardo, J.A. Gamon, P. Cuevas-Reyes. 2005. Research Priorities for Neotropical Dry Forests. Biotropica. 37(4): 477-485.

Shaker, A., Nichol, J. and Wong, M. (2008) Potential Accuracy of Image Orientation of small satellites: a case study of CHRIS-Proba data. The Photogrammetric Record 23(123):275-289.

Skole, D. & C. Tucker. 1993. Tropical deforestation and Habitat Fragmentation in the Amazon: satellite Data from 1978 to 1988. Science 260 (5116): 1905-1910.

Toledo-Aceves, T and Garcia-Olivo, F. (2008) Effects of forest-pasture edge on C, N and P associated with Caesalpinia eriostachys, a dominant tree species in a tropical deciduous forest in Mexico. Ecological Research 22 (3):271-280.

Turner W., S. Spector, N. Gardiner, M. Fladeland, E. Sterling; M. Steininger. Remote sensing for biodiversity science and conservation. 2003. Trends in Ecology & Evolution 18(6): 306-314.

UNEP. 2008. United Nations Environment Programmme: Annual report. 2008. Available at: http://www.unep.org.

United Nations. 2002. Report of the world summit on sustainable development. Johanessburg, South Africa 26 August - 4 September. Available at: http://www.johannesburgsummit.org

Ustin S., D. Roberts, J. Gamon, G. Asner; R. Green. 2004. Using Imaging Spectroscopy to study ecosystem processes and properties. BioScience 54(6):523-534.

Zelikova D. and Breed MD (2008) Effects of habitat disturbance on ant community composition and seed dispersal by ants in a tropical dry forest in Costa Rica. Journal of Tropical Ecology 24 (3):309-316

CHAPTER 2 – Integrating Remote Sensing and Biodiversity Research

INTRODUCTION

Biogeographers and ecologists have a long-standing interest in the distribution of biodiversity over different spatial and temporal scales (Gillespie et al. 2008). This interest has been driven either by the necessity to understand the basic ecological principles that govern patterns of species diversity or by the urgency to establish protected areas that preserve the majority of species in a region in the face of the global biodiversity crisis. Much of the work of practicing conservationists entails making judgments about the relative importance of different areas at a range of different scales (Sutherland, 2001). In recent years, several international conventions and agreements have stressed the importance of assessing biodiversity (Innes et al. 1998). Human activities now affect most of the terrestrial biosphere and are increasing in intensity and extent (Kerr & Ostrovsky 2003). Simultaneously, regions of the world with highest biodiversity and greatest conservation needs are often data poor (Arponen et al. 2008). Since airborne and spaceborne remote sensing data has become readily available for public and scientific use, there has been an increased interest from remote sensing researchers to measure and model biodiversity from space (Gould, 2000; Nagendra 2001; Kerr & Ostrovsky 2003; Turner et al. 2003; Gillespie et al. 2008). Even though, in the recent years, remote sensing has introduced some innovative and promising techniques to measure essential ecosystem functions and properties, these techniques are still considered as marginal prospection tools for biodiversity assessments. This perception might be caused by the lack of integration within remote sensing research itself, and between remote sensing science and the conceptual framework historically used by ecologists to understand causes and patterns of species diversity. The present work introduces a synthetic analysis on the use of remote sensing tools to measure biodiversity within the conceptual framework of biodiversity science as seen by ecologists and biogeographers. It begins by addressing the following questions: a) what is the current concept of biodiversity?, b) What factors cause and regulate biodiversity?, c) What are the most common tools and measurements used by conventional field ecology to assess biodiversity?, d) What are some remote sensing tools available and how is it used to directly assess species diversity and/or some surrogate properties of biodiversity?, and e) what are the main challenges still ahead for integrating remote sensing and biodiversity?. The objective is to highlight key terms and concepts that might be critical to unify remote sensing of biodiversity and ecological theory.

BIODIVERSITY

Defining biodiversity

Biodiversity is a term widely used by the scientific community and the general public that refers to the number of species occurring in a specific region or at global scale. The term is an abbreviated word for "biological diversity" and was first introduced during the "National Forum on Biodiversity" held at Washington DC in September 1986

(Krishnamurthy K.V. 2003). There is not single, universally accepted definition of biodiversity and it differs in scope from different authors and scientific disciplines (Kennedy 2000).

Two definitions have been widely used, since they were the outcome of agreements by several countries on global environmental protection (Krishnamurthy K.V.2003). The first definition was included in the Convention on Biological Diversity (CBD) by the United Nations (UN) and it defines biodiversity as “the variability among living, inter alia, terrestrial, marine and other aquatic systems and the ecological complexes of which they are part”. The second definition is sponsored by the Global Biodiversity Strategy and conceptualizes biodiversity as: “the totality of genes, species and ecosystems in a region”. These two concepts are broad enough to include the many levels of biological diversity and thus are capable of synthesizing the full range of entities and ecological interactions embedded within the concept of biological diversity.

According to Ziegler (2007), the most commonly understood standard definition of biodiversity among biologists always includes the following three components or levels of diversity: a) Genetic Diversity, refers to the number of different genes and alleles present within a population, a species, even an ecosystem; b) Species diversity, refers to the number of species that exist on earth, in a particular ecosystem, in a particular higher taxonomic grouping such as a phylum, etc. c) Ecosystem diversity, refers to the number of distinctly different ecosystems or communities within an area, on a continent, on the earth, etc.

These concepts of biodiversity has been criticized by various authors (World Conservation Monitoring Centre, 2000; Di Castri et al. 1996) as being imprecise and paying very little attention to the interactions within, between, and among the various levels of biodiversity recognized. Based on this concern, Di Castri et al. (1996) provided the following definition: “Biodiversity is the ensemble and the hierarchical interactions of the genetic, taxonomic and ecological scales of organization, at different levels of integration” and suggested a model for the hierarchical patterns of biodiversity (Table 2-1). According to Magurran, A.E. (2004), the term “surrogacy” has been used to explain the links between biodiversity at different levels within this hierarchy (for example; measuring habitat complexity through measures of canopy structure or stratification in a forest can be linked to species richness based on the ecological niche theory and estimating diversity at the Family level which can be used as a surrogate to understand species diversity).

Other authors have emphasized the importance of “Landscape Diversity” defined as a mosaic of heterogeneous land forms, vegetation types and land uses (Krishnamurthy K.V.2003). Noss (1994) suggested that each of these scales (genetic, species, ecosystem, and landscape) should be further subdivided into compositional, structural, and functional components (Fig 2-1). This diagram exemplifies the different levels of biodiversity existent from the patch to the global level including the interactions and hierarchical patterns between them that make the concept of surrogacy an central one when estimating biodiversity from field sampling and/or remote sensing.

Determinants of biodiversity

There are several factors that can explain the gradients of species diversity around the globe. In order to understand the potential of remote sensing as a tool to identify patterns in biodiversity, we need to sum up main factors proposed by several authors that cause gradients in species diversity. Nine different factors are discussed: time, spatial heterogeneity, competition, predation, environmental stability and predictability, primary productivity, potential evapotranspiration, intermediate levels of disturbance and geographic area.

The *Time hypothesis* is historical and emphasizes the time available for speciation and dispersal. Krohne (2001) identifies an evolutionary time hypothesis, which states that highly diverse communities have simply been in existence longer and thus have had more opportunities for species to evolve, and an ecological time hypothesis, more applicable for small-scale disturbances, that holds that high diversity communities have been stable long enough for immigration to increase the species diversity relative to younger communities. *Spatial heterogeneity* is a second factor that may influence diversity through the number of habitats available per unit area. There is a strong correlation between structural heterogeneity of a habitat and species diversity suggesting that in more structurally diverse environments, species can specialize to a greater extent on differences in microhabitats – niches - (Krohne, 2001). Krebs (1985) identifies strong effects on species diversity from macrospatial heterogeneity based factors, like topographic relief, that influences the amount of habitats in a region; and microspatial heterogeneity, related to within-habitat differences (such as vegetation structure or stratification). This factor is explained by the ecological niche theory and G. Evelyn Hutchinson's concept of an species niche as an "n-dimensional hypervolume", every point which corresponds to a state of the environment which would permit a species to exist indefinitely (Molles 2008, Ricklefs et al. 2000, Pulliam, 2000).

Competition and *Predation* are also important biological factors that influence species diversity. Competition increases in highly diverse environments such as tropical ecosystems, where structural and microclimatic diversity allows organisms to specialize into smaller niche breadths with high niche overlap between species (Krebs 1985). When competition is very intense, there will be strong selection for species to specialize in order to avoid its effects (Kronhe 2001). In contrast, *Predation* regulates competition by reducing prey populations and incrementing resource availability for new prey species to colonize. Competition and predation function as complementary factors that favor higher species diversity. The *Environmental stability and predictability* principle states that the more stable the environmental parameters, the more species will be present. When climate, for example, is stable, the rate of extinction from random effects of weather will be lower.

Another important element to evaluate is *Primary productivity.* The primary productivity factor sets a limit on the amount of energy available for use by species within a community, thus we might expect that species diversity would be limited by the productivity of the environment (Ricklefs et al. 2000). This is also known as the species-energy hypothesis. Species diversity has been found to be positively correlated to productivity, especially in some cases where resource availability is low or moderated (e.g. such as crops). Conversely, species diversity has been found negatively correlated to higher levels of primary productivity. This seems primarily caused by stronger regulation effects from biological factors, such as competition and predation, on species populations occurring in habitats with higher levels of primary productivity (Ricklefs et al. 2000). Another important factor is *Potential Evapotranspiration (PET)* which is dependant on the energy available to evaporate water and on relative humidity. Since PET is dependant on the energy available, it has been found positively correlated to species diversity and richness. Note that this close relationship found between energy availability and species diversity can be very important when using remote sensing to infer species diversity.

Furthermore, it has been suggested that *intermediate levels of disturbance* would foster high levels of diversity (Kohne, 2001). At this intermediate levels, a wide array of species can colonize open habitats, but there is not enough time for the most effective competitors to exclude the other species (Molles, 2008). The size of the habitat's *geographic area* available has been also suggested as a cause of higher diversity, where larger areas allow for greater population sizes and lower probabilities of species extinctions, more niches in which species can specialize, and larger target for isolating barriers in the speciation process (Krohne 2001). The latter is supported by the Island Biogeography Theory which in addition states that smaller islands closer to a larger island contain more species than distant ones (Ricklefs et al. 2000) This has been fundamental to understand patterns of species diversity in fragmented tropical forests (Laurance et al. 2002).

All these factors are very dynamic in space and time and can act complementarily originating a range of conditions that foster different patterns of species diversity. It is critical, for remote sensing researchers, to understand to what extent are these factors quantifiable from remote sensing, what is the potential of the tool and what are its limitations, in order to strengthen the fundamental basis of surrogate measures of biodiversity derived from remote sensing. It is also necessary to take into account the type of quantitative measurements that have been important to understand patterns and processes of species diversity. In the next section, we address how ecologists and/or biologists have historically quantified species diversity from field measurements.

Measuring biodiversity

Developing a single quantitative measurement of biodiversity, comprising the full range of entities and ecological interactions would be an impractical and difficult task, if not an impossible one. There has been, however, a need to measure indicators of biodiversity in a site, region or ecosystem, in order to study patterns at the landscape or global level. This is possible since the evidence of "surrogacy" or hierarchical relations between various organizational levels of life allows biologists to quantify biodiversity through the use of independent measures of presence, abundance and diversity of genes, species, functional types or ecosystems (Lombard et al. 2003, Arponen et al. 2008, Purvis et al. 2000, Gamon, 2008). Furthermore, assessing surrogate ecosystem structural, functional or compositional properties is possible through the use of "proxy" measurements, which are measured variables, used to infer the real value of such properties.

Biologists regard species as the fundamental units of biodiversity (Sutherland, 2000), and by measuring species diversity and species abundance of key species, are used to determine which areas are important for conservation (Lombard et al. 2003). For many population level assessments, species diversity appears the most useful general measure (World Conservation Monitoring Centre, 2000, Ziegler, 2007). Traditionally, ecologists have estimated biodiversity by three measures: (1) species richness, which is indicated by the total number of species in an area, 2) species abundance, which is indicated by the total number of individuals of a species in an area, and 3) species evenness, which represents equitability of species as given by their relative abundance (Krishnamurthy K.V.2003, Purvis et al. 2000). In addition, indices like the Shanon-Wiener Index, Simpson Index and the Fisher's alpha, which are a combination of species abundance, species richness and evenness measures, have been used to understand compositional and functional aspects in communities of species at the ecosystem level (Lamb et al., 2009, Krishnamurthy K.V.2003). These concepts are also scale-dependent. Species diversity has been described to occur in three different scales: Alpha diversity, as the number of species in an area, beta diversity as the similarity between species diversity of different areas, gamma diversity as the overall species richness within a large region (Whittaker et al. 2001).

Measuring diversity in the field in many cases requires sampling by selecting plots or transect routes located at random or in convenient areas - e.g close to roads or trails that facilitate accessibility (Sutherland, 2000). Methods include recording all species captured and observations in subsamples as small as soil sampling for invertebrates or as large as quadrats or long transects for plants, primates or amphibians to account for habitat microclimatic variability. The temporal and geographical coverage of the sampling design allows estimating different scales of diversity (Whittaker et al. 2001).

Genetic diversity can also be measured in terms of richness and evenness from field collections at the patch or landscape level. For example, Richness refers to the total number of different genotypes present in a population, while Evenness refers to the frequency of the different genotypes present in the same population. These measurements also apply for diversity of genes, DNA, chromosome properties and genetic markers (Krishnamurthy K.V. 2003, Najafzadeh et al. 2009, Lozupone et al. 2007). At the Ecosystem level, there is no authoritative index for measuring diversity since it is often evaluated through the estimation of component species richness and abundance (Krishnamurthy K.V.2003).

REMOTE SENSING

The following sections address some examples of how different remote sensing techniques and sensors have been used to infer species diversity, but first, we will introduce the fundamentals of remote sensing and the current sensors available for the task.

Remote sensing refers to the detection of electromagnetic energy from aircraft or satellites and it can be divided into wavelength regions known as "optical" and "microwave" (Turner et al. 2003, Jensen 2007). Optical remote sensing measures energy reflected and emitted from the earth's surface in wavelengths between 400 and 1400 nanometers (nm). Microwave measures much longer wavelengths that range between 1 mm and 1 m. Passive sensors measure the radiance reflected or emitted from the earth's surface to the detector, where the irradiance is often provided by the sun. Active sensors, in the other hand, emit pulses of radiation to the earth's surface and measures the energy returned or bounced back from the surface.

Optical passive sensors are usually designed to record the intensity of a signal within a wavelength interval (band or channel) at specific spectral resolutions, spatial resolutions and temporal resolutions. The width of the bands of the electromagnetic spectrum detected by a sensor determine its ability to detect spectral differences and constitute the *spectral resolution* of that instrument. Multispectral sensors can detect radiation in a few specific channels usually design to measure radiation in the Visible (VIS), Near-Infrared (NIR), Short-wave Infrared (SWIR) and thermal infrared (TIR) part of the spectrum. Imaging spectrometers (usually called "hyperspectral sensors" because of their many narrow bands) measure the reflected solar spectrum often from 350 to 2510 nm, using up to 500 contiguous bands of 5 to 10-nm bandwidths (although this is variable between hyperspectral sensors).

The *spatial resolution* is determined by the size of the minimum sampling unit, which often refers to the "pixel size" of an image. A sensor that provides 15-m spatial resolution data provides spectral information reflected from areas of 15-m x 15-m footprint in the surface. Coarse-scale resolution sensors or low spatial resolution sensors often refer to those sensors that collect information in pixel sizes greater than 1-km. Scientific researchers often refer to Moderate resolution sensors as those measuring spectral information in pixel sizes between 100-m and 1-km. High and very high spatial resolution sensors are those capable of collecting spectral information in pixel sizes ranging from 100-m to < 1m. The revisit time or temporal resolution refers to the time period between repeat passes over an object being remotely sensed (Turner et al. 2003). Typically, coarse-scale and moderate resolution sensors are multispectral and can provide greater coverage of a region (single scenes can reach up to 2600 km swath width), while high spatial sensors can be multispectral and hyperspectral but provide smaller coverage of the earth's surface (covering tenths to hundreds of kilometers in a single scene).

Radar is the one of most common active sensor types used in biodiversity studies, with the capability of sending and receiving microwave pulses in different wavelengths (i.e. X-,C- and L- bands) to create high spatial resolution images of elevation and topography based on radar backscatter or interferometric radar (Gillespie et al. 2008). Radar can penetrate cloud cover providing imagery regardless illumination or weather conditions . A summary of passive and active sensors used for biodiversity studies specifying differences spectral, spatial and temporal resolution as well as most common applications, can be found in the work from Nagendra (2001), Turner et al. (2003) and Gillespie et al. (2008).

MEASURING BIOLOGICAL DIVERSITY USING REMOTE SENSING

The use of remotely sensed data from passive and active sensors as a source of information to describe biodiversity patterns has been vast (Turner et al. 2003; Kerr & Ostrovsky 2003) and nowadays represents almost a mandatory tool to assess some critical measurements necessary for conservation planning and design (Balmford et al. 2001, Sanchez-Azofeifa et al. 2005). Depending on the object of investigation (e.g. land cover type, ecosystem property, ecosystem process, functional groups or individual species), some sensors are more capable of resolving features related to biodiversity than others and this ability is often related to the issues of scale. When identifying specific properties of ecosystems, some spectral derivates from sensors are also more useful than others (e.g. image classification, spectral indices, texture analysis). The ability to resolve properties and processes is dependent on the spatial and spectral resolution of the sensor and may also be a strong function of time in some ecosystems.

The next sections provide a description of the different techniques and sensors used to derive direct measurements or proxy measurements of biodiversity based on the aspect of biodiversity they assess: a) the extent and spatial distribution of ecosystems, b) structural diversity, c) functional and biogeochemical diversity and d) taxonomic diversity. It also discusses how techniques situate within the ecological theory that explains biodiversity.

Extent and spatial distribution of ecosystems

According to Ziegler (2007), ecosystem diversity refers to the number of ecosystems and communities in an area. Identifying the presence of an ecosystem and quantifying its extent is one of the main applications derived from remotely sensed imagery. Land cover data describes the physiographic characteristics of the surface environment, which can range from bare rock to tropical forests and that are usually derive by applying statistical clustering methods to multispectral remote sensing data (Kerr & Ostrovsky 2003). The extent and spatial distribution of ecosystems, as estimated by remote sensing, can help us understand potential species richness gradients by identifying all different types of ecosystems, the patterns of adjacency between them, and latitudinal or altitudinal differences at the global or landscape level. Identifying such components is important since these are determinants of the habitat range for certain species or functional groups based on their ecological niche width.

Our capacity to derive global ecosystem maps using remote sensing has improved with the advent of coarse and moderate resolution imagery and our understanding of the spectral properties of different land covers. Two decades ago, global and continental terrestrial ecosystem maps were derived from Global Vegetation Indices providing coarse estimates using >4 km spatial resolution imagery on ecosystem extent based on the temporal dynamics in the greenness of vegetation throughout the year (Townshend et al. 1987; DeFries & Townshend, 1994, De Fries et al. 1998, Loveland & Belward, 1997) using the Advanced Very High Resolution radiometer (AVHRR). In order to produce consistent ecosystem maps, a single source of remotely sensed information may not be enough since different types of vegetation or land uses might be better detected by using specific spectral bands and/or image processing techniques. Image processing allows the fusion of several sources to derive a single multi-source map. Eva et al. (2004) produced a land cover map of South America using remotely sensed satellite data acquired between the year 1995 and the year 2000. This research group used SWIR and thermal bands (1-km spatial resolution) from the Along Track Scanning Radiometer (ATSR-2) for differentiating between dense humid forests and seasonal forests and non-forests. Red channel, NIR, SWIR bands, and NDVI products from the SPOT VEGETATION (VGT 1-Km) sensor were used to detect seasonal vegetation formations. Radiance calibrated lights data from the Defense Meteorological Satellite Program (DMSP) Operational Linescan System (OLS) were used to locate major urban areas at 2.7 km spatial resolution. Medium resolution data was also acquired from the JERS-1 L band radar at 100 m resolution to detect permanent and seasonal flooded forests. 1600 satellite images were processed to produce a 10 classes land cover map.

Some large-scale global land cover maps are inherently unrealistic when examined closely at regional or local scales (Kalacska et al. 2005) and limit our ability to detect continuous areas of pristine ecosystems, or ecosystem remnants in fragmented landscapes. Regional and national level land cover maps showing different types of ecosystem have improved the information on local extent and geographical distribution of ecosystems and can benefit biodiversity asessment. These are usually produced after processing Landsat MSS, TM and/or ETM imagery. For example, the National Land-Cover Data (NLCD) of the conterminous United States was created from Landsat TM imagery at 30-m spatial resolution (Stehman et al. 2003). Other examples include Mas et al. (2002) who used 126 cloud-free Enhanced Thematic Mapper sensor data, acquired between November 1999 and April 2000 to produce a land cover map of Mexico; and Jones (2001) reports the results from an international effort of seven research groups in seven different countries of Central America to produce a single Ecosystem Map at a 1:250.000 scale. This map was based on 161 Landsat-5 images and classifications at the national level using data from 1979 to 1999 and produced a map representing 250 ecosystems. Land cover assessments using Landsat provide excellent results for national to local conservation and development planning (Sanchez-Azofeifa et al. 2001).

The digital output from these land cover assessments can be analyzed using geographical information systems (GIS) to detect ecosystem fragmentation patterns (Fajardo et al. 2005, Tang et al. 2005), landscape diversity, landscape structure indices (Tang et al. 2005) and land cover change (Achard et al. 2002, Nagendra et al. 2001).

The availability of techniques and sensors capable of deriving ecosystem maps at different scales, allows us to describe biodiversity through ecological theories such as the *time hypothesis*, *spatial heterogeneity*, *geographic area* and *island biogeography*. For example, time series of land cover for a specific region allows identifying and quantifying the size of small fragments of an ecosystem and their distance from larger remnants. Such an assessment allow us to infer the differences in species richness and population sizes across a fragmented landscape, based on geographic area and island biogeography theoretical principles. Land cover information complemented with topographical data can be used to identify spatially heterogeneous habitats, isolating barriers and distance from sources of disturbance which are some of the factors that determine species diversity.

Structural diversity

Beyond ecosystem mapping, there is a high interest in biodiversity science to identify spatial patterns in vegetation structure within ecosystems (e.g. height, succession, stratification). The vegetation structure can be homogenous in certain ecosystems (e.g such as grasslands, savannas, scrublands or tundra) and very complex and heterogenous in others (e.g. tropical forests). In these structurally complex ecosystems, the variation in vegetation height and stratification for example, creates larger microclimatic differences between the canopy and the understory allowing a greater number of potential niches that new species can colonize and specialize (Grimbacher et al. 2007).

Structural diversity is closely related to the *Spatial heterogeneity* factor described before which holds that macrospatial and microspatial heterogeneity are important sources of high species diversity (Kohner 2001; Ricklefs et al. 2000). Detecting gradients of structural variation within ecosystems is important since ecosystem structural variation is tightly related to species presence/absence and species diversity patterns (Townsend et al. 2008). Using direct or proxy measurements of ecosystem structure gives us the ability to infer spatial and temporal trends in species richness if we support our analyses on ecological niche theory. Indices of habitat complexity or heterogeneity like the Holdridge Complexity Index (HCI) have been used to characterize differences in plant species richness and biomass across landscapes based on compositional and structural data collected in the field (Lugo et al. 1978, Kalacska et al. 2005). Several techniques have been developed recently to detect structural variations within ecosystems using a broad range of sensors. Sources of information based in canopy roughness, shadow fraction and soil fraction are some of the tools that are used to detect the patterns of ecosystem structure (Asner et al. 2003).

For example, work by De Wasseige et al. (2002) reports the use of spatial variation of spectral values in an image (i.e. image texture or image spatial structure) to model canopy texture. According to De Wasseige et al. (2002), NIR reflectance band of Landsat TM and SPOT satellites provide a good picture of canopy variability. They also report other approaches for prediction of canopy structure using multi-angular reflectance data from various high spatial resolution sensors. Peddle et al. (1999) used spectral mixture analysis to determine areal fractions of sunlit canopy, sunlit background, and shadow at subpixel scales in order to predict biophysical and structural variability in boreal forests using a Landsat TM spectral band simulator (Modular Multi-band Radiometer). Shadow fraction provided the best results at predicting structural variations in these canopies. Asner et al. (2003) used 44 IKONOS images and simulated Landsat observations and found out that shadow fraction products from both Red and NIR wavelengths regions work as good predictors of top-of-canopy biophysical structure in tropical forests. They also found that shadow fraction products derived from the visible (e.g. red) of the spectrum are able to predict canopy variability in savanna ecosystems. Pasher et al. (2007) also used shadow fractions to detect gaps in the forest in order to predict nesting sites for the hooded warbler (*Wilsonia citrina*) with a mapping accuracy of 70%, using IKONOS and Landsat imagery. Leboeuf et al. (2007) found a significant relationship between shadow fraction products derived from Quickbird imagery and above-ground biomass of boreal forests. Similarly, soil fraction mapping from high resolution imagery has been used to detect differences in vegetation abundance (Wessman et al. 1997, Gilabert et al. 2000). These assessments have provided information especially from the canopy level of the ecosystem.

A deeper exploration of habitat structure has been provided by active remote sensing systems. Active systems like LIDAR (Light Detection and Ranging) sensors are capable of using their return signals to detect the height of the canopy top, ground elevation, and the positions of leaves and branches in between (Turner et al. 2003). The Laser Vegetation Imaging Sensor (LVIS), for example, is a lidar sensor that has been used to collect return-signals coming from the top of the canopy and vegetation in the understory of tropical forests in Costa Rica providing information on the number and height of forest strata (Weishampel et al. 2000, Castillo et al. 2008.). Airborne VCL and helicopter-borne scanning lidar systems have been used over boreal and tropical ecosystems to derive ecosystem vertical structure and total volume of biomass (Drake et al. 2002, Ni-Meister et al. 2001, Lefsky et al. 2002a, Omasa et al. 2003). Further examples of LIDAR applications for ecosystem research can be found in Lefsky et al. (2002b). Backscattering information extracted from radar interferometry (lnSAR) and L-band / P-band radar measurements is sensitive to vegetation moisture and vertical structure and it has been demonstrated as an useful tool to estimate biomass, forest height and other vertical dimensions of forests (Chambers et al. 2007, Ranson et al. 1997, Santos et al. 2003). Canopy structure and vertical structure complexity of ecosystems are one of the most important determinants of species diversity (Kohner, 2001), therefore further remote sensing research in this field might improve its use as a proxy measurement of potential biodiversity in a region.

Furthermore, structural changes to pristine ecosystems following disturbances foster the colonization of new species creating highly heterogeneous intermediate stages with high species diversity (Molles, 2008). The ability of sensors and image processing techniques to detect differences in structural properties of ecosystems is also helpful for identifying those intermediate stages. As mentioned before, *Intermediate levels of disturbance* fosters greater species diversity by relaxing interspecific interactions such as competition and predation. Linking our capacity to detect structural variability within ecosystems to this hypothesis allows us to distinguish spatial patterns of habitat diversity and species diversity.

For example, using remote sensing to map vegetation successional stages and disturbed ecosystems allows us to identify spatial distribution of these disturbance stages having higher number of species. This information would be very helpful for conservation and restoration practices. Several authors have reported remote sensing techniques useful for this task. For example, Kalacska et al. (2005) and Arroyo-Mora et al. (2005) used Leaf Area Index (LAI) measurements in tropical forests sites and Red/NIR spectral information from Landsat 7 ETM+ and IKONOS bands and spectral indices to discriminate between successional stages of tropical dry forests. Previous work by Foody et al. (1996) also succeeded in separating successional stages using the Red and NIR wavelengths. Using Landsat 4 MSS, Hall et al. (1991) previously reported some correspondence between boreal forest successional stages and spectral values in the Green band and the NIR band. Thomson et al. (2004) demonstrated the detection of salt-marsh vegetation successional change driven by erosion/accretion processes by analyzing multitemporal the Compact Airborne Spectrographic Imager (CASI) imagery for an estuary in the Netherlands. Neeff et al. (2005) used backscatter information from SAR to detect differences in forest biomass related to forest successional stages for the Brazilian Amazon. Other recent research on successional vegetation mapping by using remote sensing can be found in the works of Neeff et al. (2006), Song et al. (2007), Kalacska et al. (2007), McDonald et al. (2007) and Hartter et al. (2008).

Functional and Biochemical diversity

Ecosystem functions such as primary productivity, potential evapotranspiration, and biochemical properties such as pigment and nutrient concentration have been linked to species richness and diversity (Ricklefs et al. 2000, Asner et al. 2008). Whether there is a direct causal relationship between these ecosystem properties and species diversity is not clear, since each one can drive or foster each other reciprocally (Kohner, 2001). However, there is no doubt that there is a close linkage between field or remotely sensed measurements of several functional and biochemical properties and species diversity. Understanding global, regional and local spatial patterns of functional and biochemical properties using a broad array of sensors has been an important task for remote sensing scientists.

Functional diversity

Spatially-explicit models of functional diversity have resulted from the development and use of Vegetation Indices. The contrast between high chlorophyll absorption in the VIS regions of the spectrum (400-700 nm) and the high scattering of radiation from vegetation canopies in the NIR region of the spectrum has given way to the development of a set of spectral indices that characterize this contrasting reflectance pattern into indices of vegetation abundance (Gamon et al. 1999). One of the most commonly used spectral indices is the Normalized Difference Vegetation Index (NDVI), which is calculated from spectral values in the Red and NIR regions of the spectrum reflected from a target in a landscape. NDVI values have been successfully correlated to the Fraction of Absorbed Photosynthetically Active Radiation (FAPAR), which is the amount of energy in the VIS region of the spectrum that is absorbed, by any type of land cover. Several vegetation properties such as leaf area, levels of disturbance, light-use efficiency and other environmental or physiological factors determine the FAPAR of a region. FAPAR is an essential component for the estimation of ecosystem Net Primary Productivity (NPP), which is an indicator of carbon fixation efficiency from photosynthetic processes. Both NPP and FAPAR are dependent on the energy available for photosynthetic processes, and correlate with Potential Evapotranspiration (PET) which is dependent on the energy available to evaporate water (Ricklefs et al. 2000). These three ecosystem functions, NPP, FAPAR and PET, are linked and respond similarly to solar irradiance patterns. This linkage justifies the use of NDVI as a "*surrogate*" measure of both NPP and PET since it correlates strongly with the absorbed photosynthetically active radiation (Kerr & Ostrovsky 2003; Kooistra et al. 2008).

The use of NDVI derived from multispectral and hyperspectral airborne and spaceborne imagery has been used to derive local and global models of FAPAR and NPP (Running, 2004). Recent studies suggest that the MODIS-derived Photochemical Reflectance Index (PRI), based on contrasting reflectance between specific wavelengths within the VIS spectrum (the 531 nm and 570 nm wavelengths), can further improve NPP models by providing a better measure of ecosystem light use efficiency (Grace et al. 2007, Drolet et al. 2008). NDVI models derived from remote sensing have been also proven successful for linking global photosynthetic processes to atmospheric CO_2 content (Chong et al. 1993, Gamon et al. 1999). Futher information on the theoretical approach of remote sensing to derive models of photosynthetic production can be found in Gamon et al. (1999).

Understanding spatial patterns of such ecosystem functions across landscapes allows us to predict gradients in carbon gain, leaf area index and even species diversity based on the species-energy theory (This subject will be discussed in next section). The use of NDVI models has also been helpful to understand how ecosystem functions vary, not only in space, but also through time (e.g. seasons, years, decades). Results from Reed et al. (1994) showed strong coincidence between AVHRR-NDVI values collected continuously over several years and predicted phenological characteristics (e.g. start of the growing season, end of the growing season, rate of greenup, rate of senescence) among several land cover types in the USA. Similarly but using higher spatial resolution imagery, Fisher et al. (2005) collected 57 Landsat scenes from 1984 to 2002 and analyzed greenness patterns associated with leaf-onset differences among ecosystems and rural areas in Southern New England, USA. Functional diversity across landscapes and even within ecosystem patches can be used to assess landscape or even global levels of biodiversity by predicting *spatial heterogeneity* of ecosystem processes and *intermediate levels of disturbance*. The power to observe these phenomena through time and space allows us to predict the effects of *environmental stability and predictability* on species richness as well.

Biochemical diversity

Measuring canopy biochemical diversity can also assess these determinants of biodiversity. For the detection and mapping of ecosystem biochemical properties, most research has focused on the spectral properties of leaves and canopies that provide estimates of photosynthetic pigments, water, dry matter and nitrogen (Ustin et al. 2004).

Jensen (2007) provides a comprehensive guide through the fundamental principles that govern the spectral properties of different vegetation pigments (chlorophylls, carotenoids, flavonoids, cellulose) and water. The dynamics of plant pigments relate strongly to the physiological status of plants, therefore information concerning the temporal and spatial variations of pigments can be a valuable indicator of a range of key ecosystem properties and processes (Blackburn, 2007).

Much of the work related to biochemical properties of vegetation resulted in the development of spectral indices that show strong relationships with pigments, water content and other biologically important elements (Gamon et al. 1999, Darvishzadeh et al. 2008). For example, Huang et al. (2004) successfully estimated foliage nitrogen content from the Australian woodlands in Canberra using narrow band indices from HyMAP data. Rao et al. (2008) found a positive correlation between spectral data derived from EO-1 Hyperion hyperspectral sensor and chlorophyll and leaf nitrogen content. Based on the results, they proposed a Plant Biochemical Index (PBI) using the 810 and 560 nm wavelengths. Although their experiment was applied in agricultural crops, the index has the potential for assessing biochemical temporal and spatial variability in canopies of different ecosystems. Fuentes et al. (2001) estimated relative concentrations of chlorophylls, anthocyanins and carotenoids at the landscape level for boreal forest stands using the Photocehmical Reflectance Index (PRI) calculated from AVIRIS narrow bands. For a summary on the spectral properties of plant biochemical components and the diverse spectral indices developed to measure its content from field spectroscopy and remote sensing, see Gamon et al. (1999), Ustin et al. (2001) and Jensen (2007).

All of these assessments have underpinned the ability of remote sensing to detect and model ecosystem function and biochemical properties, but few and very recent research has been dedicated to study the potential of these factors, as measured from remote sensing, to predict patterns in species richness. The work from Townsend et al. (2008) and Asner et al. (2008) suggest that chemical, physiological and structural variation of tropical forest canopies is driven by taxonomic diversity. This concept is based on the *spatial heterogeneity* factor as a driver of biodiversity. Invoking the concept of “surrogacy”, Gamon (2008) suggests that measures of “optical diversity” and structure from biophysical and biochemical sensitive spectral bands should link with independent measures of in-situ species diversity. Few studies have investigated the power of canopy spectral diversity to biodiversity measurements. Asner et al. (2008) reports findings of a strong correlation between species richness, a chemical diversity index and a spectroscopic diversity index using leaf reflectance measurements. The integration of spatial models of pigment content, nutrient content, and canopy biochemical heterogeneity derived from remote sensing would allow us to map resource availability in order to infer niche breadths, species diversity, and even competition patterns across landscapes. Further studies have linked biochemical and biophysical diversity in tropical forests to its taxonomic composition, suggesting that individual species can be mapped through biochemical diversity mapping (Carlson et al. 2007, Asner et al. 2008). This subject will be addressed in the following section which is focused on mapping individual species and species richness from remote sensing.

Taxonomic diversity

This section presents a summary of efforts made using proxy measurements from remote sensing to make direct predictions of species diversity (e.g. ecological niche modeling and NPP-based approaches) along with efforts on the detection of individual species using high spatial and spectral resolution remote sensing.

Ecological Niche modeling

Identifying species habitat preferences, modeling species habitat distribution and mapping individual species and/or associations has been a challenging task of remote sensing research for conservation biologists. Each species ecological niche entail specific requirements on the ranges of conditions and resource qualities within which the organism can persist (Riklefs et al. 2000), therefore predicting species presence/absence and species richness has improved by introducing remote sensing derived models of environmental and physical constraints to potential species distribution.

In the last 20 years, species distribution modeling, also known as ecological niche modeling, has incremented (Gillespie et al. 2008, Zhao et al. 2006). Pioneer studies like the one by Wallin et al. (1992) used spectral information from AVHRR to map and monitor potential habitat for an African bird (*Quelea quelea*) using NDVI and species presence/absence data. Further research suggested that Ecological niche modeling required species survey data and associated environmental measurements, an understanding of ecological theory, and robust statistical models (Austin et al. 1996). Since then, there has been an increment in research being made on the comparison of statistical models, constraints, assumptions and nature of survey data (Brotons et al. 2004,). Multiple software and statistical models are available for biologist to model species distribution such as the Ecological Niche Factor Analysis (ENFA), the Generalised Linear Models (GLM), the Canonical Correspondence Analysis (CCA), Biomapper, MAXENT, and the Genetic Algorithm for Rule-set Production (GARP) among others. These models use constraints based on habitat distribution and vegetation indices, which are outputs from remotely sensed imagery. Sensors used depend on the scale of the study. For example, Buermann et al. (2008) used optical and microwave remote sensing data from the sensors MODIS and Quikscat (QSCAT) along with climatic information to map the geographical distribution of eight Tropical Andes species (two birds, two mammals and four trees) at 1-km spatial resolution. Zhao et al. (2006) used species presence, temperature, precipitation, soil moisture data along vegetation maps derived from Landsat TM imagery to assess the distribution of the Qinghai spruce on a locality of northwest China.

NPP-based approaches

As mentioned in the section 2.2, Net primary Productivity (NPP) is a surrogate measure of species diversity according to the *species-energy hypothesis* that states that high primary productivity corresponds to greater resource availability and therefore allows for increased specialization and greater diversity of species per unit area (Feeley et al. 2005, Bailey et al. 2004, Currie 1991, Oindo et al. 2002). Given that vegetation indices are associated with net primary productivity (Chong et al. 1993), they have been used as proxies to assess patterns of species diversity and floristic composition (Turner et al. 2003, Gillespie et al. 2005, Feeley et al. 2005).

For example, Phillips et al. (2008) found strong positive correlation between NDVI / NPP models derived from MODIS and native landbird species richness data from the North American Breeding Bird Survey. Their results also showed lower species richness at higher NPP values which seems consistent with the species-energy hypothesis. Gould (2000) also found that variation in NDVI is positively correlated with measured plant species richness and a weighted abundance of vegetation types in the Hood river region of the Canadian Arctic. However, results are not always consistent across ecosystems and this may be a factor influenced by differences in ecological processes occurring in different ecosystems, differences in the taxa studied, and disparities in the techniques used when analyzing spectral information from remote sensors. Oindo et al. (2002) found that higher average AVHRR NDVI actually results in lower species richness, but standard deviation and coefficient of variation measure did correlated positively with species richness in the savanna grasslands of southern Kenya. Bailey et al. (2004) found positive relationships between maximum NDVI and the number of functional guilds of birds and butterflies. In contrast to Oindo et al. (2002), Bailey et al. (2004) found negative correlation between heterogeneity of NDVI and species richness derived from Landsat TM in sagebush and woodland vegetation types of the great basin of western USA.

The work by Fairbanks et al. (2004) in the chaparral, scrub, woodland and forests ecosystems in California found that species richness was correlated to AVHRR NDVI but the linearity and the positive or negative correlation of the fitting curve was influenced by the type of ecosystem and the year of NDVI data suggesting that time frame of the analysis is also an important factor. Other work by Feeley et al. (2005) and Gillespie (2004) found positive correlation between NDVI extracted from Landsat ETM+ imagery and plant species richness in tropical dry forest ecosystems. Using Landsat, ASTER and Quickbird imagery, Levin et al. (2007) found a positive significant correlation between plant species richness and NDVI values from all these sensors. Moreover, other indices based on Red/NIR ratios have also been positively correlated with plant species richness and structure. Kalacska et al. (2005) reports varied positively correlations between several vegetation indices (such as the Modified Single Ratio or MSR; the Simple ratio or SR, and the Soil-Adjusted Vegetation Index 2 or SAVI2) and species abundance.

Generally, spectral indices are good predictor of species richness (Phillips et al. 2008, Gillespie, 2003, Feeley et al. 2005, Kalacska et al. 2005) and is well supported on the species-energy hypothesis, however, further research is needed in order to understand how species diversity is related to NDVI measurements across different ecosystems (e.g. from lower structural complexity ecosystems like savannas, tundra or scrublands to highly complex ecosystems such as tropical rainforests) using sensors with variable spectral and spatial resolution. It is important to understand field-based ecological knowledge of primary productivity and species richness in a broad range of ecosystems and taxonomic levels in order to make coherent predictions of biodiversity patterns using spectral analysis techniques that are consistent with ecological theory.

Mapping individual species

Ecologists and biologists identify species on the field and count individuals from each species in order to provide a complete species inventory in a community. These inventories are used to compare species richness, species abundance and species evenness across gradients in the same ecosystem or across different ecosystems. Beyond using remote sensing products as proxies to estimate species richness, there is an increasing desire to directly identify and map species within landscapes from high-resolution spaceborne sensors that have been launched in recent years (Gillespie et al. 2008).

For example, the work by Nagendra (2001) summarizes some early efforts in mapping individuals and associations of pine, spruce, fir, beech, and herbaceous species using conventional image classifiers (i.e. Maximum Likelihood, Parallelepiped algorithms) and reports the limitations and low-accuracy results from several studies using early sensors and aerial photography. The launch of new commercial satellites with very high spatial resolution sensors in the recent years such as the multispectral IKONOS and Quickbird has improved our capability to identify individual crowns and species assemblages (Turner et al. 2003). Sidle et al. (2002) were able to visually detect small and large colonies of the black-tailed prairie dog (*Cynomys ludovicianus*) using IKONOS imagery. Fuller (2005) detected aggregation patterns at the landscape level of an invasive species stands in South Florida using also IKONOS imagery. Wang et al. (2004) successfully classified mangrove species by including canopy textural roughness data from IKONOS and Quickbird. High spatial resolution imagery is also a promising tool for studies at the tree crown level and could improve our understanding off the spatial dimensions of phenological changes such fruiting events and/or leaf senescence at the patch or landscape level (Turner et al. 2003, Clark et al. 2004).

The development and availability of hyperspectral sensors (such as EO-1 Hyperion) adds greater potential for species separability since they have sufficiently narrow bandwidths to resolve individual absorption features in reflectance spectra (Gamon, 2008). Hyperspectral sensors open new possibilities for measuring species diversity and detecting the presence of individuals from certain species within a given area. Some examples include the work by Voss et al. (2008) who successfully differentiated seven tree species in an urban environment using hyperspectral data from the Airborne Imaging Spectroradiometer for Applications (AISA) and LIDAR data. Buddenbaum et al. (2005) used classification algorithms over HyMAP hyperspectral data to map the distribution of tree species of coniferous forests in western Germany. Andrew et al. (2008) also used HyMAP image data to detect and map the distribution of an invasive species in the Californian Delta Estuary.

Carlson et al. (2007) and Asner & Martin (2009) suggested a method to predict plant species richness from airborne hyperspectral sensors (AVIRIS and HiFIS) based on spectral diversity in wavelength regions associated with upper-canopy pigments, water and nitrogen content. Carlson et al. (2007) analyzed hyperspectral signatures from 17 tropical forest sites with species richness values ranging from 1 to 17 species per 0.1-0.3 ha, and found that increasing spectral diversity was linked to increasing species richness by way of increasing biochemical diversity. Based on these findings and following the same methods, Asner et al. (2008) further analyzed hyperspectral signatures related to specific chemical fingerprints of plant functional groups, family, genus, and even species. Their approach, refered as “spectranomics”, resulted successful for mapping the distribution of invasive *Ficus* species in Hawaiian forests. These studies have been only conducted using AVIRIS and HiFIS hyperspectral sensors in lowland tropical forest ecosystems in Hawaii, which means there is a need to explore its application across different ecosystems using other sensors. However, these findings suggest that using biochemical diversity as a surrogate might be a powerful way to predict species diversity at the landscape level. This new approach, based in chemistry, physics and taxonomy of canopies could change how ecosystems are measured, monitored and managed (Asner et al. 2008).

The potential to estimate the number of species richness in an ecosystem from remote sensing suggests that results from field methods conducted by ecologists and biologists can be compared for specific sites to those derived from remote sensing, especially when some sensors have the ability to match the spatial resolution at which field sampling is being made. Once validated, remote sensing approaches could then be used to estimate species richness by using the quadrat or transect method over hyperspectral imagery. This could help to expand the capabilities of field ecologists to conduct species surveys at regions of difficult accessibility and to understand continuous spatial patterns of species diversity at the landscape level in order to plan more efficient biodiversity conservation and management practices.

INTEGRATING REMOTE SENSING AND BIODIVERSITY RESEARCH

Biodiversity is often quantified based on discrete stratified sampling of species richness, species abundance and evenness. Global or local conservation priorities are usually defined from overlapping species potential distributions and richness patterns with potential habitat extent (Myers et al. 2000). While this information is useful for understanding regional or global patterns, effective conservation action at the local to landscape level would benefit greatly from detailed information of how species diversity is distributed within a mountain, a prairie or a tropical forest remnant. In this context, remote sensing provides the possibility of transition from a discrete source to a continuous source of spatial information on species diversity, ecosystem processes and patterns. Remote sensing could also be used to detect relative diversity or to detect “hotspots” of biodiversity globally or across a local landscape. The launch of many new satellite systems over the recent decade and the development of new technologies, some available only on airborne platforms, have given us unprecedented number of remote sensing tools with which to address the challenge of predicting biodiversity patterns (Turner et al. 2003).

Understanding the linkage between spectral information and biodiversity is still a challenging and exciting task that depends on our ability to find the best “surrogate” ecological measurement of biodiversity (from a single or multiple ecosystem properties) that can be efficiently and accurately modeled from remote sensing products. From the conventional three components or levels of diversity: genetic, species and ecosystem diversity (Ziegler, 2007); remote sensing can directly provide information for two of them. Ecosystem diversity in one hand, which refers to the number of ecosystems in an area, has been achieved by means of land cover characterization through imagery classification techniques. Land cover maps have been derived for global assessments using coarse-scale information (sensors that collect data using 8-km to 500-m minimum mapping resolution), and for local assessments using high resolution imagery (using 60-m to 1-m minimum mapping resolution). Extent estimates and fragmentation patterns can be used to estimate the number of fragments above or below the minimum area requirements to support viable populations for particular species (Rodriguez et al. 2006). This information complemented with topographical data can be used to quantify landscape heterogeneity, isolating barriers and distance from sources of disturbance, which are important determinants of species diversity. The second, species diversity, has been estimated by using proxy measurements of structural, functional and biochemical diversity which function as surrogates. Spatial variation of spectral values related to canopy spectral variability, spectral fractions of sunlit canopy, soil background and tree shadows, lidar and radar direct measurements of canopy structure and vertical vegetation stratification, have been used as predictors of canopy heterogeneity and structural diversity, which is considered one of the most important determinants of species diversity. Recent research using hyperspectral sensors has been also linking plant species diversity in tropical forests and spectral diversity in wavelength regions associated with upper-canopy biochemical properties (e.g. N,P,water, pigments) with some success. Direct prediction of species diversity has been also achieved through the use of high spatial resolution imagery capable of successfully discriminating between individual tree crowns. Genetic diversity has been less easily addressed by remote sensing. Nonetheless, as scientific research continuous to advance in assessing species composition (at the individual species level or family level), then this information can be used as a surrogate measure for genetic diversity.

One of the main limitations from previous and current research on remote sensing of biodiversity comes from the tradition of developing techniques by using a single sensor with specific spectral and spatial resolution, radiometric calibration parameters, and angular sensor position relative to target. There has been little effort to upscale or downscale proxy measurements of species richness from spectral assessments using different spatial resolutions, spectral resolutions and sensor technical parameters. Such evaluations could allow upscaling the usual patch or landscape level assessments of ecosystem structural and biogeochemical properties to derive global or regional models. Conversely, downscaling approaches could be applied to investigate apparent hotspots of biodiversity identified in coarse-resolution imagery. In general, hyperspectral sensors with high spatial resolution seem to have a greater potential for mapping proxies of species richness, and mapping individual species as well, since they can resolve both chemical composition and structural features (Gamon 2008). The use of narrow bandwidths from hyperspectral sensors is also useful for evaluating specific wavelengths as successful predictors in an experimental context; and can be used to design new sensors of regional to global coverage that include bandwidths that are sensitive to relevant surrogate ecosystem properties of species richness. Other limitations of the current knowledge on remote sensing of biodiversity is that most assessments have been performed for a particular location, or vegetation type, so there has been little replication across ecosystems of the remote sensing techniques applied. Since different ecosystems have different structural properties and physiological processes, we should design sound scientific methods to identify the most suitable sensors and processing techniques that would allow us to make comparable assessments through diverse landscapes.

Most predictive models to date lack of sufficient post-processing validation with independent ground species richness or ecosystem properties information and, when conducted, such validation is rarely explicitly presented or conducted in a manner that is acceptable to ecologists. It has been suggested that in order to make progress, ecologists must bring their datasets on species distributions, levels of species richness, areas of endemism, and so on, to the table and combine them with datasets generated by remote sensing researchers (Turner et al. 2003), however, I would suggest that interdisciplinary teams combine their efforts in providing relevant species richness measures, or ecosystem structural and biogeochemical information that is detectable from remote sensing, using standardized concepts that are common between ecologists and remote sensing researchers in order to move the discipline forward into unifying goals in biodiversity science and conservation.

Given the current biodiversity crisis, the increasing intensity and extent of human activities and the prospect for increasing climate change altering habitats around the world, there is an urgent need to define conservation priorities of species and species interactions from the local to the global level. Contrary to other disciplines, remote sensing has the unique capability of producing continuous datasets of environmental information in a consistent format. Rather than generating new remote sensing tools based on isolated experiments from isolated research teams, integrating remote sensing and biodiversity science should be the upcoming task of interdisciplinary teams of ecologists and remote sensing researchers around the globe. It is important to conciliate the concepts and ecological theory that explains the spatial and temporal patterns of biodiversity and the remote sensing tools we use, in order to achieve consistent, coherent and thus, useful predictive models of biodiversity applicable using a wide range of sensors over a wide range of ecosystems.

TABLE LEGENDS

TABLE 2-1 Scales of organization and Levels of interactions proposed by Di Castri & Younes (1996).

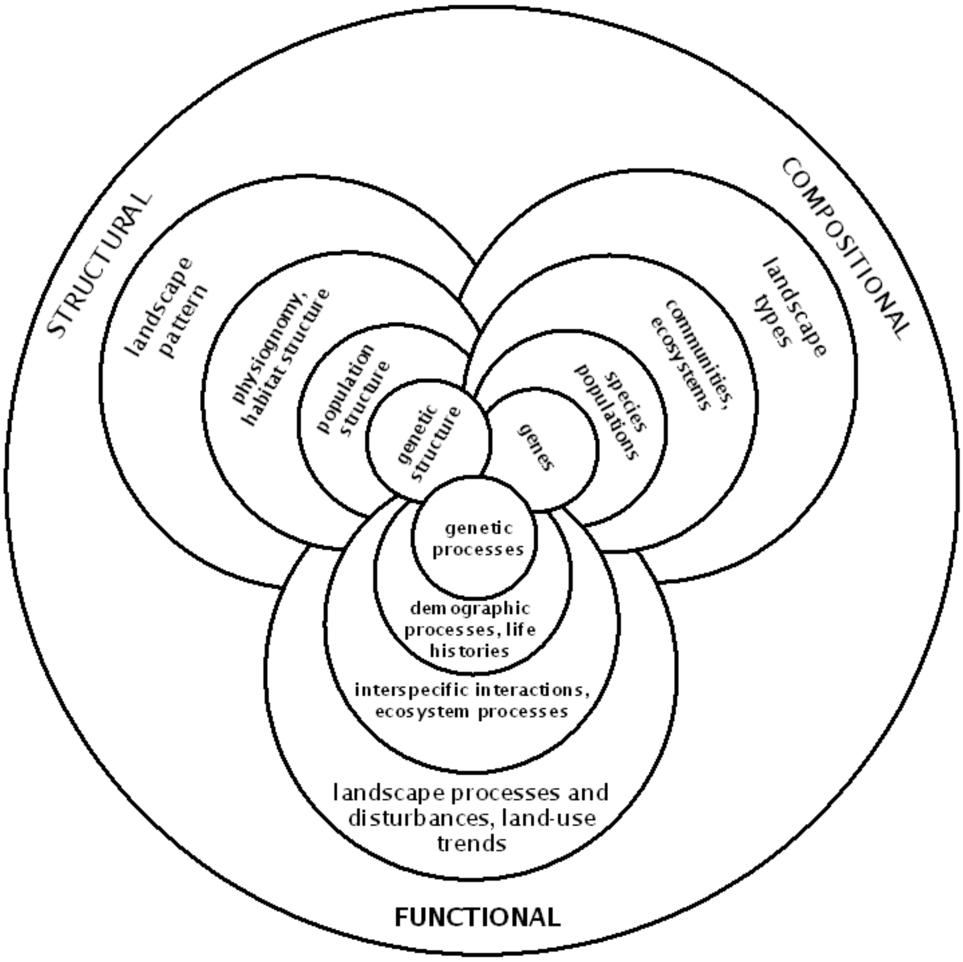
FIGURE LEGENDS

FIGURE 2-1. The biodiversity concept incorporating the multiple levels of organization at different spatial and temporal scales, by Noss (1994).

(Table 1)

	Scales of organisation		
	Genetic Diversity	Species Diversity	Ecosystem Diversity
Levels of interaction	Community Population Individual organism Cell Molecule	Kingdom Phylum Class Order Family…. Species…	Biosphere Biome Ecosystem Patch Habitat

(Figure 1)


STRUCTURAL
COMPOSITIONAL
FUNCTIONAL
landscape pattern
physiognomy, habitat structure
population structure
genetic structure
landscape types
communities, ecosystems
species populations
genes
genetic processes
demographic processes, life histories
interspecific interactions, ecosystem processes
landscape processes and disturbances, land-use trends

LITERATURE CITED

Achard, F., H. D. Eva, H.-J. Stibig, P. Mayaux, J. Gallergo, T. Richards, and J.-P. Malingreau. 2002. Determination of deforestation rates of the world's humid tropical forests. Science 297 (5583):999-1002

Andrew, M.E. and S.L. Ustin. 2008. The role of environmental context in mapping invasive plants with hyperspectral image data. Remote Sensing of Environment 112(12): 4301-4317.

Arponen, A., A. Moilanen, and S. Ferrier. 2008. A successful community-level strategy for conservation prioritization. Journal of Applied Ecology 45(5):1436-1445.

Arroyo-Mora, J.P.; G.A. Sanchez-Azofeifa, M. Kalacska, B. Rivard, J.C. Calvo-Alvarado and D. Janzen, 2005. Secondary forest detection in a neotropical dry forest landscape using Landsat 7 ETM+ and IKONOS imagery. Biotropica 37(4): p. 497-507.

Austin, M.P. and J.A. Meyers. 1996. Current approaches to modelling the environmental niche of eucalypts: Implication for management of forest biodiversity. Forest Ecology and Management 85(1-3): 95-106.

Asner, G.P. and A.S. Warner . 2003. Canopy shadow in IKONOS satellite observations of tropical forests and savannas. Remote Sensing of Environment 87(4):521-533.

Asner, G.P., M.O. Jones, R.E. Martin, D.E. Knapp and R.F. Hughes. 2008. Remote sensing of native and invasive species in Hawaiian forests. Remote Sensing of the Environment 112: 1912–26.

Asner, G.P. and Martin R. 2009. Airborne spectranomics: mapping canopy chemical and taxonomic diversity in tropical forests. Frontiers in Ecology and the Environment. 7(5): 269-276.

Bailey, S.A., M.C. Horner-Devine, G.A. Luck, L.A. Moore, K.M. Carney, S. Anderson, C. Betrus, and E. Fleishman. 2004. Primary productivity and species richness: Relationships among functional guilds, residency groups and vagility classes at multiple spatial scales. Ecography 27:207-217.

Balmford, A., L. Bennun, B., Brink, D. Cooper, I.M. Côté, P. Crane, A. Dobson, N. Dudley, I. Dutton, R.E. Green, R. Gregory, J. Harrison, E.T. Kennedy, C. Kremen, N. Leader-Williams, T. Lovejoy, G. Mace, R. May, P. Mayaux, J. Phillips, K. Redford, T.H. Ricketts, J.P. Rodriguez, M. Sanjayan, P. Schei, A. van Jaarsveld, & B. A. Walther. 2005. The Convention on Biological Diversity's 2010 target. Science 307: 212-213.

Blackburn, G.A. 2007. Hyperspectral remote sensing of plant pigments. Oxford Univ Press.

Brotons, L., W. Thuiller, W., Araújo, M.B. & Hirzel, A.H. 2004. Presence-absence versus presence-only modelling methods for predicting bird habitat suitability. Ecography 27(4): 437-448.

Buddenbaum, H., M. Schlerf, and J. Hill. 2005. Classification of coniferous tree species and age classes using hyperspectral data and geostatistical methods. International Journal of Remote Sensing 26(24):5453-5465.

Buermann, W., S. Saatchi, T.B. Smith, B.R. Zutta, J.A. Chaves, B. Mila, and C.H. Graham. 2008. Predicting species distributions across the Amazonian and Andean regions using remote sensing data. Journal of Biogeography 35(7): 1160-1176.

Carlson, K.C., G.P. Asner, R.F. Hughes, R. Ostertag, and R.E. Martin. 2007. Hyperspectral remote sensing of canopy biodiversity in Hawaiian lowland rainforests. Ecosystems 10(4): 536-549.

Castillo, M. (2009) Detection of successional stages and spatial patterns of forest initiation strategies for an abandoned Tropical Dry Forest pasture in Guanacaste, Costa Rica. Thesis submitted to the Faculty of Graduate Studies and Research for the degree of Master of Science. Department of Earth & Atmospheric Sciences, University of Alberta. Edmonton,Canada.

Clark, D.B., J.M. Read, M.L. Clark, A.M. Cruz, M.F. Dotti; D.A. Clark. 2004. Application of 1-M and 4-M resolution satellite data to ecological studies of tropical rain forests. Ecological Applications 14(1): 61-74.

Chambers, J.Q.; G.P. Asner; D.C. Morton; L.O. Anderson; S.S. Saatchi, D.B. Espirito-Santo, M. Palace, and C. Souza Jr. 2007. Regional ecosystem structure and function: ecological insights from remote sensing of tropical forests. Trends in Ecology & Evolution 22(8):414-423.

Chong, D.L.S.; E. Mougin; J.P. Gastelluetchegorry. 1993. Relating the Global Vegetation Index to Net Primary Productivity and Actual Evapotranspiration over Africa. International Journal of Remote Sensing. 14(8):1517-1546.

Currie, D.J. 1991. Energy and large-scale patterns of animal species and plant species. American Naturalist 137(1):27-49.

Darvishzadeh, R.; A.K. Skidmore, M. Schlerf; C.G. Atzberger; M.A. Cho. 2008. LAI and chlorophyll estimation for a heterogeneous grassland using hyperspectral measurements. Isprs Journal of Photogrammetry and Remote Sensing 63(4): p. 409-426.

DeFries, R. S., & Townshend, J. R. G. 1994. NDVI-derived land cover classifications at a global scale. International Journal of Remote Sensing 15(17): 3567-3586.

DeFries, R.; Hansen, M.; Townshend, J.; Sohlberg, L. 1998. Global land cover classifications at 8 km spatial resolution: the use of training data derived from Landsat imagery in decision tree classifiers. Int. J. Remote Sensing 19 (16): 3141- 3168

De Wasseige, C. and P. Defourny. 2002. Retrieval of tropical forest structure characteristics from bi-directional reflectance of SPOT images. Remote Sensing of Environment 83(3):362-375.

Di Castri, F. and Younes, T. 1996. Biodiversity Science and Development.Towards a New partnership. CAB International & IUBS, Wallingford, U.K., pp. 1-11. [Cited from Krishnamurthy, K.V. 2003]

J.B. Drake, R.O. Dubayah, D.B. Clark, R.G. Knox, J.B. Blair, M.A. Hofton, R.L. Chazdon, J.F. Weishampel; S. Prince. 2002. Estimation of tropical forest structural characteristics using large-footprint lidar. Remote Sensing of Environment 79(2-3): p. 305-319.

Drolet, G.G., E.M. Middleton, K.F. Huemmrich, F.G. Hall, B.D. Amiro, A.G. Barr, T.A. Black, J.H. McCaughey; H.A. Margolis. 2008. Regional mapping of gross light-use efficiency using MODIS spectral indices. Remote Sensing of Environment 112(6): 3064-3078.

Eva, H D., A.S. Belward; E.E. De Miranda; C.M. Di Bella, V. Gond.; O. Huber, S. Jones, M. Sgrenzaroli; S. Fritz. 2004. A land cover map of South America. Global Change Biology 10 (5), 731-744.

Fairbanks, D.H.K. and K.C. McGwire (2004) Patterns of floristic richness in vegetation communities of California: regional scale analysis with multi-temporal NDVI. Global Ecology and Biogeography 13(3): p. 221-235.

Fajardo, L, V. González; J.M. Nassar; P. Lacabana; C.A. Portillo; F. Carrasquel; J.P. Rodríguez. 2005. Tropical Dry Forests of Venezuela: Characterization and Current Conservation Status. Biotropica 37 (4), 531-546.

Friedl, M.A.; C. Brodley. 1997. Decision Tree Classification of Land Cover from Remotely Sensed Data. Remote Sensing of Environment 61:399-409

Feeley, K.J., T.W. Gillespie, J.W. Terborgh. 2005. The utility of spectral indices from Landsat ETM+ for measuring the structure and composition of tropical dry forests. Biotropica 37(4):508-519.

Foody, G.M.; Palubinsakas, G.; Lucas, R.M.; Curran, P.J.; Honzak, M. 1996. Identifying terrestrial carbon sinks: Classification of successional stages in regenerating tropical forest from Landsat TM data. Remote Sensing of Environment 55(3): p. 205-216.

Fuller, D.O. 2005. Remote detection of invasive Melaleuca trees (Melaleuca quinquenervia) in South Florida with multispectral IKONOS imagery. International Journal of Remote Sensing 26(5):1057-1063.

Fisher, J.I., J.F. Mustard; M.A. Vadeboncoeur. 2006. Green leaf phenology at Landsat resolution: Scaling from the field to the satellite. Remote Sensing of Environment 100 (2): 265-279.

Friedl, M.A; Brodley, C.A and Strahler, A.H. 1999. Maximizing Land Cover Classification Accuracies Produced by Decision Trees at Continental to Global Scales. IEEE Transactions on Geoscience and Remote Sensing 37(2).

Friedl, M.A.; D.K. McIver; J.C.Hodges; X.Y. Zhang; D. Muchoney; A.H. Strahler; C.E. Woodcock, S. Gopal; A. Schneider; A. Cooper; A. Baccini; F. Gao; C. Schaaf. 2002. Global land cover mapping from MODIS: algorithms and early results. Remote Sensing of Environment 83: 287–302

Fuentes, D.A.; J.A. Gamon, H.-L. Qiu, D.A. Sims; D.A. Roberts. 2001. Mapping Canadian boreal forest vegetation using pigment and water absorption features derived from the AVIRIS sensor. Journal of Geophysical Research-Atmospheres 106(D24): p. 33565-33577.

Gamon, J.A., Qiu, H-L. 1999. Ecological applications of remote sensing at multiple scales. pp. 805-846 In: Handbook of Functional Plant Ecology. Pugnaire FI, Valladares F. (Eds) Marcel Dekker, Inc. New York.

Gamon J.A. 2008. Tropical Remote Sensing – Opportunities and Challenges. In: Hyperspectral Remote Sensing of tropical and sub-tropical forests. 1st Ed. Taylor and Francis Group, pp. 297-304.

Gilabert, M.A., F.J. Garcia-Haro; J. Melia. 2000. A mixture modeling approach to estimate vegetation parameters for heterogeneous canopies in remote sensing. Remote Sensing of Environment 72(3):328-345.

Gillespie, T.W. 2005. Predicting woody-plant species richness in tropical dry forests: A case study from south Florida, USA. Ecological Applications 15(1):27-37.

Gillespie, T.W., G.M. Foody, D. Rocchini, A.P. Giorgi, and S. Saatchi. 2008. Measuring and modelling biodiversity from space. Progress in Physical Geography 32 (2): 203-221.

Gould, W. 2000. Remote sensing of vegetation, plant species richness, and regional biodiversity hotspots. Ecological Applications 10(6):1861-1870.

Giri C; Jenkins, C. 2005. Land cover mapping of Greater Mesoamerica using MODIS data. Can. J. Remote Sensing 31(4): 274-282.

Grace J, C. Nichol, M. Disney, P. Lewis, T. Quaife, P. Bowyer. 2007. Can we measure terrestrial photosynthesis from space directly, using spectral reflectance and fluorescence? Global Change Biology 13(7): 1484-1497.

Grimbacher, P.S.; N.E. Stork. 2007. Vertical stratification of feeding guilds and body size in beetle assemblages from an Australian tropical rainforest. Austral Ecology 32(1):77-85.

Hansen, M.C.; R.S. Defries, J.R.G. Townshend. 2000. Global land cover classification at 1km spatial resolution using a classification tree approach. International Journal of Remote Sensing 21 (6-7):1331-1364.

F.G. Hall, D.B. Botkin, D.E. Strebel, K.D. Woods and S.J. Goetz. 1991. Large scale patterns of forest succession as determined by remote sensing. Ecology 72 (2): 628.

Hartter, J.; Lucas, C.; Gaughan, A.E.; Aranda, L.L. 2008. Detecting tropical dry forest succession in a shifting cultivation mosaic of the Yucatan Peninsula, Mexico. Applied Geography 28(2): 134-149.

Huang, Z., Turner, B.J., Dury, S.J., Wallis, I.R., Foley, W.J. 2004. Estimating foliage nitrogen concentration from HYMAP data using continuum removal analysis. Remote Sensing of Environment 93(1-2): p. 18-29.

Innes, J.L. and B. Koch. 1998. Forest biodiversity and its assessment by remote sensing. Global Ecology and Biogeography **7**(6): p. 397-419.

Jensen, J . 2007. Remote Sensing of Environment: an earth resource perspective. 2nd Edition. Prentice Hall Series in Geographic Information Science. Pearson Prentice Hall, USA.

Jones, J.R. 2001. Processing of digital data for the Central American Ecosystem map. Available from: http://mitchnts1.cr.usgs.gov/data/worldbank/metadata/WB%20Ecosystem%20Map%20CA%20Process.pdf. [Cited 23 October 2005]

Kalacska, M., et al. 2007. Ecological fingerprinting of ecosystem succession: Estimating secondary tropical dry forest structure and diversity using imaging spectroscopy. Remote Sensing of Environment 108(1): p. 82-96

Kalacska, Margaret E. R., Sánchez-Azofeifa, G. Arturo, Calvo-Alvarado, Julio C., Rivard, Benoit & Quesada, Mauricio. 2005. Effects of Season and Successional Stage on Leaf Area Index and Spectral Vegetation Indices in Three Mesoamerican Tropical Dry Forests. Biotropica 37 (4), 486-496.

Kennedy, P.W. 2000. Managing Biodiversity: Policy issues and challenges. Working paper, John Deutsch Institute for the study of Economic Policy, Queens University.

Kerr, J.T.; M. Ostrovsky. 2003. From space to species: ecological applications for remote sensing. Trends in Ecology & Evolution 18(6): p. 299-305.

Kooistra, L., Wamelink, W., Schaepman-Strub, G., Schaepman, M., van Dobben, H., Aduaka, U., Batelaan, O. 2008. Assessing and predicting biodiversity in a floodplain ecosystem: Assimilation of net primary production derived from imaging spectrometer data into a dynamic vegetation model. Remote Sensing of Environment 112(5):2118-2130.

Krishnamurthy, K.V. 2003. Textbook of biodiversity. Science Publishers, Inc.Enfield, NH. USA.

Krebs, C .1985. Ecology: the experimental analysis of distribution and abundance. 3rd Edition. University of British Columbia. Harper & Row Publishers, NY.USA.

Krohne, D. 2001. General Ecology. 2nd Edition. Brooks Cole/Thomson Learning. USA.

Lamb, E.G.; E. Bayne, G. Holloway, J. Schieck, S. Boutin, J. Herbers and D.L. Haughland. 2009. Indices for monitoring biodiversity change: Are some more effective than others? Ecological Indicators 9(3): 432-444.

Laurance, L.; T.E. Lovejoy, H.L. Vasconcelos, E.M. Bruna, R.K. Didham, P.C. Stouffer, C. Gascon, R.O. Bierregaard, S.G. Laurance, E. Sampaio. 2002. Ecosystem Decay of Amazonian Forest Fragments: a 22-Year Investigation. Conservation Biology 16 (3):605-418.

Leboeuf A., A. Beaudoin, R.A. Forunier, L. Guindon, J.E. Luther and M.-C. Lambert. 2007. A shadow fraction method for mapping biomass of northern boreal black spruce forests using QuickBird imagery. Remote Sensing of Environment 110: 488–500

Lefsky, M. A., W. B. Cohen, D. J. Harding, G. G. Parker, S. A. Acker; S.T. Gower. 2002. Lidar remote sensing of aboveground biomass in three biomes. Global Ecology and Biogeography 11: 393-399.

Lefsky, M. A., W. B. Cohen, D. J. Harding and G. G. Parker. 2002. Lidar remote sensing for forest ecosystem studies. BioScience 52: 19-30.

Levin, N., A. Shmida; O. Levanoni; H. Tamari; S. Kark. 2007. Predicting mountain plant richness and rarity from space using satellite-derived vegetation indices. Diversity and Distributions 13(6): 692-703.

Lombard, A.T., R.M. Cowling; R.L. Pressey; Rebelo, A.G. 2003. Effectiveness of land classes as surrogates for species in conservation planning for the Cape Floristic Region. Biological Conservation, 2003. 112(1-2):45-62.

Loveland, T., Merchant, J.W., Brown, J.F., Ohlen, D.O., Reed, B., Olson, P., Hutchinson, J. (1995) Seasonal Land Cover Regions of the United States. Annals of the Association of American Geographers 85 (2): 339-355

Loveland TR, Belward AS.1997. The International Geosphere Biosphere Programme Data and Information System global land cover data set (DISCover). ACTA ASTRONAUTICA 41 (4-10): 681-689.

Lozupone, C. A., M. Hamady, S. T. Kelley, and R. Knight. 2007. Quantitative and qualitative beta diversity measures lead to different insights into factors that structure microbial communities. Applied and Environmental Microbiology 73(5):1576-1585.

Lugo A E, Gonzalez-Liboy J A, Cintron B and Dugger K. (1978) Structure, Productivity and Transpiration of a sub-tropical dry forest in Puerto Rico. Biotropica 10(4): p. 278-291.

Magurran, A.E. .2004. Measuring biological diversity. Oxford: Blackwell Science.

Mas JF, Velazquez A, Palacio-Prieto JL, Bocco G, Peralta A, Prado J. 2002. Assessing forest resources in Mexico: Wall-to-wall land use/cover mapping Photogrammetric Engineering and Remote Sensing 68 (10): 966-968

McDonald, R.I., P.N. Halpin, and D.L. Urban. 2007. Monitoring succession from space: A case study from the North Carolina Piedmont. Applied Vegetation Science 10(2): 193-202.

Molles, M. 2008. Ecology: concepts and applications. 5th Edition. McGraw-Hill Science/Engineering/Math. USA.

Muchoney, D.; Borak, J., Chi, H., Friedl, M., Gopal, S., Hodges, J. Morrow, N and Strahler, A. 2000. Application of the MODIS global supervised classification model to vegetation and land cover mapping of Central America. Int. J. Remote Sensing 21 (6 & 7): 1115-1138.

Myers, N.; Mittermeier, R.; Mittermeier, C.; Da Fonseca, G. & Kent, J. 2000 Biodiversity hotspots for conservation priorities. Nature 403: 853-858.

Nagendra, H. . 2001. Using remote sensing to assess biodiversity. International Journal of Remote Sensing 22(12):2377-2400.

Nagendra, H., D.K. Munroe, and J. Southworth. 2004. From pattern to process: landscape fragmentation and the analysis of land use/land cover change. Agriculture Ecosystems & Environment 101(2-3):111-115.

Najafzadeh, M.J., C. Gueidan, H. Badali, A. H. G. Gerrits Van Den Ende, Lian Xi, G. S. De Hoog. 2009. Genetic diversity and species delimitation in the opportunistic genus Fonsecaea. Medical Mycology 47(1): p. 17-25.

Neeff, T., L. V. Dutra, J. R. Santos, C. C. Freitas; L. Araújo. 2005. Tropical forest measurement by interferometric height modeling and P-band radar backscatter. Forest Science 51(6):585-594.

T., R. Neff, M. Lucas, J. R. Dos-Santos, E. S. Brondizio; C. C. Freitas. 2006. Area and age of secondary forests in Brazilian Amazonia 1978-2002: An empirical estimate. Ecosystems 9(4):609-623.

Ni-Meister, W., D.L.B. Jupp, and R. Dubayah. 2001. Modeling lidar waveforms in heterogeneous and discrete canopies. Ieee Transactions on Geoscience and Remote Sensing 39(9):1943-1958.

Noss, R.F. 1994. Hierarchical indicators for monitoring changes in biodiversity.Essay 4A. In: Meffe, G.K. and Carroll, C.R. (Eds) Principle of Conservation Biology. Sinauer Associates, Sunderland, Mass., USA, pp.79-80. [Cited from Krishnamurthy, K.V. 2003]

Oindo, B.O.; A.K. Skidmore. 2002. Interannual variability of NDVI and species richness in Kenya. International Journal of Remote Sensing 23(2):285-298.

Omasa K, GY Qiu, K. Watanuki, K. Yoshimi, Y. Akiyama. 2003. Accurate estimation of forest carbon stocks by 3-D remote sensing of individual trees. Environmental Science & Technology 37(6): 1198-1201.

Pasher, J., D. King, and K. Lindsay. 2007. Modelling and mapping potential hooded warbler (Wilsonia citrina) habitat using remotely sensed imagery. Remote Sensing of Environment 107(3): 471-483.

Peddle, D.R., F.G. Hall, and E.F. LeDrew. 1999. Spectral mixture analysis and geometric-optical reflectance modeling of boreal forest biophysical structure. Remote Sensing of Environment 67(3): 288-297.

Phillips, L.B.; Hansen A.J.; Flather C. H. 2008. Evaluating the species energy relationship with the newest measures of ecosystem energy : NDVI versus MODIS primary production. Remote Sensing of Environment 12 (9):3538-3549.

Pulliam, H.R. 2000. On the relationship between niche and distribution. Ecology Letters, 3: 349-361.

Purvis, A. and A. Hector. 2000. Getting the measure of biodiversity. Nature 405(6783): 212-219.

Ranson, K. J., G. Sun, J.F. Weishanpel, R.G. Knox. 1997. Forest biomass from combined ecosystem and radar backscatter modeling. Remote Sensing of Environment 59(1):118-133.

Reed BC, JF Brown, D. VanderZee, TR Loveland, JW Merchant, DO Ohlen. 1994. Measuring Phenological Variability from Satellite Imagery. Journal of Vegetation Science 5(5):703-714.

Ricklefs, R. & Miller, GL. 2000. Ecology. 4th Edition. Chiron Press. USA.

Rao, N.R.; P.K. Garg; S.K. Ghosh, V.K. Dadhwal. 2008. Estimation of leaf total chlorophyll and nitrogen concentrations using hyperspectral satellite imagery. Journal of Agricultural Science 146:65-75.

Rodriguez, JP; Balch, J. & KM Rodriguez-Clark. 2006. Assessing extinction risk in the absence of species-level data: quantitative criteria for terrestrial ecosystems. Biodiversity and Conservation. 16 (1):183-209.

Running, S; Ramakrishna, R.N, Heinsch, F.A; Zhao, M.; Reeves, M & Hashimoto, H. 2004. A continuous Satellite-derived measure of Global Terrestrial Primary Production. Bioscience 54(6):547-560.

Sanchez-Azofeifa, G.A. Harris, R.; Skole, D. 2001. Deforestation in Costa Rica: a quantitative analysis using remote sensing imagery. Biotropica 33(3): 378-384.

Sánchez-Azofeifa, G.A., Quesada, M., Rodríguez, J.P., Nassar, J.M., Stoner, K.E., Castillo, A., Garvin, T., Zent, E.L., Calvo-Alvarado, J.C., Kalacska, M., Fajardo, L., Gamon, J.A., Cuevas-Reyes, P. 2005. Research Priorities for Neotropical Dry Forests. Biotropica. 37(4): 477-485.

Santos, J.R.; Freitas, C.C.; Araujo, L.S.; Dutra, L.V.; Mura, J.C.; Gama, F.F.; Soler, L.S.; Sant'Anna, S.J.S. 2003. Airborne P-band SAR applied to the aboveground biomass studies in the Brazilian tropical rainforest. Remote Sensing of Environment 87(4): 482-493.

Sidle, J.G., D.H. Johnson, B.R. Euliss, M. Tooze. 2002. Monitoring black-tailed prairie dog colonies with high-resolution satellite imagery. Wildlife Society Bulletin 30(2): p. 405-411.

Song, C., T.A. Schroeder, and W.B. Cohen. 2007. Predicting temperate conifer forest successional stage distributions with multitemporal Landsat Thematic Mapper imagery. Remote Sensing of Environment 106(2):228-237.

Tang, J., L. Wang, and S. Zhang. 2005. Investigating landscape pattern and its dynamics in Daqing, China. International Journal of Remote Sensing 26(11):2259-2280.

A.G. Thomson, A. Huiskes, R. Cox, R.A. Wadsworth and L.A. Boorman. 2004. Short-term vegetation succession and erosion identified by airborne remote sensing of Westerschelde salt marshes, The Netherlands. International Journal of Remote Sensing 25(20): 4151-4176.

Townshend, J., Justice, C., Kalb, V. 1987. Characterization and classification of South American Land Cover Types. International Journal of remote Sensing. 8:1189-1207

Townsend, A.R., G.P. Asner, and C.C. Cleveland. 2008. The biogeochemical heterogeneity of tropical forests. Trends in Ecology & Evolution 23(8):424-431.

Turner W., S. Spector, N. Gardiner, M. Fladeland, E. Sterling; M. Steininger. Remote sensing for biodiversity science and conservation. 2003. Trends in Ecology & Evolution 18(6): 306-314.

UNEP.1995. Global Biodiversity Asessment. Cambridge Univ. Press. Cambridge. [Cited from Krishnamurthy, K.V. 2003]

Voss, M. and R. Sugumaran. 2008. Seasonal effect on tree species classification in an urban environment using hyperspectral data, LiDAR, and an object-oriented approach. Sensors 8(5):3020-3036.

Wang, L., Sousa, W. P., Gong, P. 2004. Comparison of IKONOS and QuickBird images for mapping mangrove species on the Caribbean coast of Panama. Remote Sensing of Environment, 91(3-4): 432-440.

Wallin, D.O., C.C.H. Elliott, H.H. Shugart, C.J. Tucker and F. Wilhelmi. 1992. Satellite remote-sensing of breeding habitat for an african weaverbird. Landscape Ecology 7(2): 87-99.

Weishampel, J.F. Blair, J.B.; Dubayah, R.O.; Clark, D.B. 2000. Volumetric lidar return patterns from an old-growth tropical rainforest canopy. International Journal of Remote Sensing 21(2): p. 409-415.

Wessman, C.A., C.A. Bateson; T.L. Benning. 1997. Detecting fire and grazing patterns in tallgrass prairie using spectral mixture analysis. Ecological Applications 7(2):493-511.

Whittaker, R.J., K.J. Willis, and R. Field. 2001. Scale and species richness: towards a general, hierarchical theory of species diversity. Journal of Biogeography 28(4): 453-470.

World Conservation Monitoring Center. 2000. Global Biodiversity: Earth’s living resources in the 21st century. By: Groombridge, B. and Jenkins, M.D. World Conservation Press, Cambridge, U.K.

Zhao C.; N. Zhongren; C.Guodong; Z. Junhua; F. Zhaodong. 2006. GIS-assisted modelling of the spatial distribution of Qinghai spruce (Picea crassifolia) in the Qilian Mountains, northwestern China based on biophysical parameters. Ecological Modelling191(3-4): p. 487-500.

Ziegler, D. 2007. Understanding Biodiversity. Praeger Publishers, WestPort, CT.USA.

CHAPTER 3 - Extent and Conservation of Tropical Dry Forests in the Americas

INTRODUCTION

Tropical dry forests are among the most threatened ecosystems in the world as a consequence of intensive anthropogenic disturbance converting half of its extent to other land uses (Janzen, 1988; Hoekstra, 2005). Ewel (1999) explains that in this particular ecosystem, the environmental constraints on human development are low in comparison to others. Here, annual rainfall does not deviate greatly from potential evapotranspiration, irrigation water is needed in modest amounts, yet rainfall is not so high that pest and nutrient leaching are overbearing problems (Ewel, 1999). This ecosystem has historically supported high human population densities given that its climatic and edaphic characteristics are attractive for human settlement and development in the tropics (Tosi & Voertman, 1964; Sanchez-Azofeifa et al. 2005). Furthermore, most scientific efforts for the study and conservation of tropical vegetation have focused on tropical rain forests, while little attention has been paid to tropical dry forests despite its high species richness and endemism of woody plants, especially in continental and oceanic islands (Trejo & Dirzo. 2000; Sanchez-Azofeifa et al. 2005, Gillespie et al. 2003, Kier, 2005).

Several authors have defined tropical dry forests in different ways, based on similar or different criteria. Mooney et al. (1995) defines the tropical dry forest simply as forests occurring in tropical regions characterized by pronounced seasonality in rainfall distribution with several months of drought. Sanchez-Azofeifa et al. (2005) describes tropical dry forests as a vegetation type typically dominated by deciduous trees where at least 50% of trees present are drought deciduous, the mean annual temperature is ≥25°C, total annual precipitation ranges between 700 and 2000 mm, and there are three or more dry months every year (precipitation < 100 mm). Pennington et al. (2006) uses a wider interpretation of tropical dry forests which includes vegetation that experience a minimum dry season period of 5-6 months with concomitant strongly seasonal ecological processes and functions. This definition includes diverse formations such as forests within grasslands, shrublands and savanna ecosystems; from tall forests on the more humid dry forest sites to cactus scrub on the driest. Sanchez-Azofeifa et al. (2005) also considers savannas, gallery forests, coastlines and mangroves among the associated vegetation types that can occur within the matrix of tropical dry forests. Despite the many different definitions, it is essential to map the extent and geographical distribution of these important tropical forest formations.

More than half of tropical dry forests occur in the Americas (approximately 54%, according to Miles et al. 2006). These are referred to as Neotropical dry forests. At present, Neotropical dry forests exist as fragments of a once large, contiguous forest that reached from Mexico to Northern Argentina, reduced primarily by the timber industry, indigenous fuel-wood extraction, and the expansion of cattle ranching (Fajardo et al. 2005). In spite of our awareness of the rapid destruction of dry forests, we still know very little about the true current extent and degree of fragmentation of Neotropical dry forests.

Coarse-scale resolution maps (>1 km spatial resolution) based on the analysis of multispectral imagery from sensors like AVHRR (Advanced Very High Resolution Radiometer), SPOT (Systeme Pour l'Observation de la Terre) and MODIS (Moderate Resolution Imaging Spectroradiometer) have provided comprehensive global views of the distribution of Neotropical dry forests. Nonetheless, when examined closely, these maps are inaccurate and tend to overestimate the extent of tropical humid forests and underestimate the extent of tropical dry forests. Such errors affect the accuracy of carbon stocks estimates based on forest maps, which are essential for the implementation of conservation strategies such as the Payments for Environmental Services (PES) initiatives (Kalacska et al. 2005). Limitations to these analyses include spatial resolution, image classification methodology, the tropical dry forest definition used, and also imagery selection procedures that do not account for latitudinal differences in leaf phenology patterns (differences in the date of the range and peak of the dry season and wet season). Until now, there has not been a ground-truthed map derived from moderate-resolution imagery that focuses exclusively on Neotropical dry forests at the regional level and addresses the issues that might affect the assessment of the current extent of these forests. The development of a comprehensive map of Neotropical dry forest coverage is therefore especially important as a first step toward understanding the dry forest conservation status among different countries in the Americas (Sanchez-Azofeifa et al. 2005). Providing a land cover assessment of Neotropical dry forests would allow the scientific community to understand the dry forest distribution patterns and improve knowledge on the location of potential restoration areas or new reserves.

The purpose of this paper is to report the results of an assessment of the current extent of Neotropical dry forests based on MODIS surface reflectance imagery at 500-m resolution. The analysis focuses on tropical dry forest ecosystems that fall within the floristic, zoogeographic and bioclimatic parameters suggested by Olson et al. (2001) and by Sanchez-Azofeifa et al. (2005) for North America, Central America, the Caribbean islands and South America. Imagery selection in this work accounts for latitudinal differences in phenology and provides an accuracy assessment for validation. We also included forests outside the strict tropical dry forest biome limits by mapping the extent of forests within important associated savannas, grasslands and shrublands ecosystems such as the Chaco Dry Forests, Caatinga, Cerrado, the Llanos and other savannas in South America which are considered areas where dry forest species could potentially occur (Miles et al. 2006). We also analyzed fragmentation patterns and degree of protection at continental, sub-continental and national levels, and discussed implications for forest management and conservation.

METHODS

Definition of Tropical Dry Forest

Rather than limiting our study to a single definition of tropical dry forest, our analysis intends to examine the extent of tropical dry forest in a broad sense. We took into account main bioclimatic and phenological characteristics as indicated by several authors (Olson et al. 2001, Sanchez-Azofeifa et al., 2005, Pennington et al. 2006, Mooney et al. 2005), which are more relevant from the remote sensing point of view. Bioclimatic constraints for tropical dry forests were used by the adopting Olson et al. (2001) global biomes classification and Sanchez-Azofeifa et al. (2005) dry forest definition. Patterns of leaf phenology were also crucial during the image classification process in order to differentiate the spectral response of deciduous vegetation from the spectral response of evergreen vegetation and also from other types of land use. The use of tropical dry forest biome boundaries by Olson et al. (2001) and information on the patterns of leaf phenology during the image-processing phase is further explained in the next section.

The definition of tropical dry forest proposed by Olson et al. (2001) excludes deciduous vegetation types that authors consider part of the dry forest ecosystem. For example, caatinga forest is characterized as low height forest consisting mostly of small deciduous trees and shrubs, frequently displaying twisted trunks and thorns (Queiroz, 2006). Due to ecological and floristic similarities, Pennington et al. (2000, 2006) considers caatinga vegetation as part of the Neotropical dry forests. However, Olson et al. (2001) classifies this region as a shrubland ecosystem. The Olson et al. (2001) definition of dry forest neither includes deciduous vegetation in savannas nor Dry Chaco vegetation as part of the distribution of tropical dry forests. Yet the Llanos savannas, the Beni savannas, the Campos Rupestres savannas and the Cerrado all contain scattered fragments of deciduous forests, mostly related to soil fertility and moisture gradients (Fajardo et al. 2005, Pennington et al. 2000, 2006). The Dry Chaco ecosystem is also considered by some authors as part of the Neotropical dry forests (Gentry 1995, Eva et al. 2004 and Gasparri et al. *In press*), although Prado (1993) considers that the Chaco vegetation has more floristic similarities with temperate dry formations and therefore, this ecosystem should be excluded from the definition of tropical dry forest.

In order to represent tropical dry forest under a range of possible definitions, we focused the assessment on the extent and conservation of Neotropical dry forests using the geographical boundaries defined by Olson et al. (2001) for the dry forest biome, and separately, report the extent and conservation status of forests within the tropical savannas biome (which includes tropical savannas and Dry Chaco vegetation) and the caatingas from the desert and xeric shrublands biome. Although our assessment adopts the Olson et al. (2001) geographical constraints for potential dry forest distribution, extending the analyses to include ecologically and floristic related savannas, woodlands and shrublands will allow the scientific community to determine the extent and conservation of Neotropical dry forest using wider definitions of tropical dry forests as well. Importantly, rather than climate, the biome delineation by Olson et al. (2001) is a result of the exploration of existing global maps of floristic, zoogeographic provinces and broad vegetation types, and the consultation of regional experts; unlike most classifications available (Miles et al. 2006).

Study Area

In order to map the current extent of Neotropical dry forests, it was necessary to acquire and process MODIS imagery within the potential distribution of tropical dry forest in the Americas. The assessment by Olson et al. (2001) of the geographic distribution of the world's biomes includes tropical dry forests under a category named "tropical and subtropical dry broadleaf forests". The geographic data is available to the public and scientific community as a vector data layer for geographic information systems (GIS). By performing a GIS overlay between the dry forest biome data layer and climatic data from Global Historical Climatology Network (GHCR) (Vose et al. 1992), we found that the biome layer encompasses land cover areas with a mean annual precipitation of 1048 mm (ranging from 108 mm to 2050 mm) and a mean annual temperature of 23°C (ranging from 14°C to 27°C). This climatic range is similar to the one suggested by Sanchez-Azofeifa et al. (2005) for tropical dry forests. The GIS layer also allows to analyze results by ecoregions within the tropical dry forest biome, which can be useful to highlight distinctive areas that are worthy of greater attention (Olson et al. 2001). Therefore, the study area was constrained by the geographical boundaries of the "tropical and subtropical dry broad-leaf forest" biome available as a GIS data layer and made available by Olson et al. (2001). We have analyzed the distribution of forests within the "tropical and subtropical grasslands, savannas and shrublands" biome (which includes savannas and Dry Chaco vegetation) and the Caatinga ecoregion from the "Desert and Xeric shrublands" biome (Olson et al. 2001). We report the results separately in order to differentiate trends across floristic, ecological and physiognomic types of dry forests. All three biome boundaries comprise deciduous vegetation existing in 34 ecoregions and correspond to deciduous vegetation within 15 countries across continental America (Argentina, Bolivia, Brazil, Colombia, Costa Rica, Ecuador, El Salvador, Guatemala, Honduras, Mexico, Nicaragua, Panama, Paraguay, Peru and Venezuela) and 5 countries in the Caribbean islands (Cayman Islands, Cuba, Dominican Republic, Haiti and Jamaica). All biomes and ecoregion boundaries are part of a larger mosaic carved from the original ecosystem that currently includes other land uses such as agriculture, urban development and pasture lands.

General approach

We acquired MODIS visible and infrared reflectance data from the dry season of year 2004 at 500-m spatial resolution (accounting for latitudinal shifts in precipitation patterns) along with ancillary data (elevation, aspect, slope) and subset it geographically according to the biome boundaries described above. Then we identified and categorized the range of spectral reflectances representing tropical dry forest, caatinga, woodlands in the cerrado savannas and dry Chaco vegetation as well as non-forest land cover classes in MODIS imagery. To do this, we digitized ground control points for all land cover types by exploring higher resolution imagery (Landsat TM and ETM+ and Google Earth products). The MODIS spectral reflectance data collected at these ground control locations were used as input for the machine learning / decision tree imagery classification approach that was applied to classify the MODIS imagery in land cover classes. All vegetation detected was cross-checked for consistency and coherence with higher resolution data. We chose a minimum mapping unit of 100-ha (1-km^2) for the final map. Materials and methods applied are further explained in the following sections.

Imagery Acquisition

In 1998, onboard the Terra Platform, NASA launched the first Moderate Resolution Imaging Spectroradiometer (MODIS) instrument, providing improved capabilities for terrestrial satellite remote sensing aimed at meeting the needs of global change research (Justice et al., 1998). The design of the land imaging component combines characteristics of the AVHRR and the Landsat Thematic Mapper sensors, adding middle and long-wave infrared (IR) spectral bands, and providing spatial resolutions at 250 m, 500 m and 1-km global coverage with a near-daily imaging capacity.

The imagery used for this analysis included the first seven bands from MODIS-Terra surface reflectance daily L2G Global data and the first seven bands from MODIS-Terra surface reflectance 8-Day L3 Global composites data. For mapping tropical dry forest extent and structure in a landscape, the use of imagery collected during the dry season has proven successful since dry forest structural properties are more pronounced and distinctive during the dry season (Kalacska et al. 2007). This allows tropical dry forest areas to be discerned from semi-deciduous and from evergreen gallery forests within the tropical dry forest matrix. The use of dry season imagery also improves the chances of acquiring cloud-free imagery.

For the selection of imagery within the dry season, we performed an inspection of monthly satellite-derived vegetation indices (e.g. the MODIS-Terra Vegetation Indices 16-day L3 Global 1 KM SIN GRID product) for the year 2004 and explored differences in dry forest phenology patterns within the biogeographical limits of the Neotropical dry forest. We used published rainfall data to differentiate precipitation patterns across the region. For tropical North and Central American regions, we identified imagery from mid-April 2004 (April 10th and April 24th) to provide the best scenes (low cloud cover) from the dry season. For the northern Andean countries and the Caribbean Islands, imagery was selected from mid-January 2004 (January 25th and January 17th, respectively). For countries south of the Amazon basin, imagery was selected from the end of August 2004 (specifically, August 28th). MODIS Vegetation Indices 16-Day L3 Global 500m imagery was also acquired for the same dates of the year 2004. The MODIS imagery obtained was mosaicked and reprojected from sinusoidal projection to GCS-WGS84 using the MODIS Reprojection Tool (available from http://lpdaac.usgs.gov/).

Ancillary data

We acquired continuous surface elevation data at a 1-km spatial resolution, derived from the Shuttle Radar Topography Mission (SRTM), in order to include elevation, aspect and slope as independent variables in the classification. The SRTM data are available from the Global Land Cover Facility (GLCF) website (http://www.landcover.org). For the derivation of training sites or ground control points, we acquired 17 Landsat TM and ETM+ dry season scenes from the GLCF website. These images cover tropical dry forest landscapes in Mexico, Costa Rica, Bolivia, Venezuela, Colombia, Brazil, Argentina and the Caribbean Islands. A different set of four Landsat ETM+ scenes were used as a source for selecting validation sites for the final map accuracy assessment in dry forest landscapes of Mexico, Venezuela, Bolivia and Brazil.

Collection of Ground Control Points

We collected a total of 10655 locations from ancillary data (Landsat Imagery) over tropical dry forests landscapes in Mexico, Costa Rica, Bolivia, Venezuela, Colombia, Brazil, Argentina, and the five Caribbean islands. These locations were used as ground control points during the classification process. Points representing forest and non-forest were collected by interpretation of raw Landsat data and vegetation indices derived from the same Landsat scenes. We selected a separate set of control points to represent woodlands in the Cerrado, Caatinga forests, and Dry Chaco forests. The high-resolution imagery available for visualization on Google Earth (http://earth.google.com) was also helpful for the collection of training sites.

The collection of ground control points addressed the fact that dry forest landscapes are mosaics of successional stages, e.g. the product of natural or human-induced disturbances through time. For this reason, it was necessary to select deciduous forest control points over a variable range of environmental gradients, topographical characteristics and distances to urban and agricultural areas in order to account for differences in chronological age and land use history. As a result, the dry forest extent estimates produced in this analysis represent old growth dry forests as well as different successional stages of altered dry forests within the potential tropical dry forest biome distribution. The spatial resolution of MODIS imagery used for this analysis might have made the detection of early successional stages of dry forests a more difficult task. Early successional forests primarily consist of sparse patches of woody vegetation, shrubs and pastures including a single stratum of tree crowns reaching a maximum height of approximately 6-8 m (Arroyo-Mora et al. 2005). Given the extreme diversity of the land cover matrix (Castro et al. 2003) and the amount of pasture land and bare soil exposed, pixels presenting either early succesional stage dry forests or highly disturbed forests have a higher probability of being included in the non-forest class. The map herein primarily represents old growth and intermediate stages of dry forests with little to moderate structural disturbance.

Dry deciduous vegetation can also be found within tropical humid and subhumid biomes or xeric shrubland biomes as a result of localized variations of topography, soil and climate. However, since we constrained the analysis to specific geographical regions where dry forest bioclimatic characteristics predominate; potential local occurrences of dry forests in humid and xeric biomes were not included. This approach was necessary in order to maintain coherence with the bioclimatic ranges and potential distributions proposed by previous authors (Sanchez-Azofeifa et al. 2005; Pennington et al. 2006; Olson et al. 2001).

Imagery Classification

We subset the acquired imagery and ancillary data, to the extent of the "tropical and subtropical broadleaf forest" and the "tropical and subtropical grasslands, savannas and shrublands" biome boundaries. Additionally, we co-registered all imagery and ancillary data to 500-m pixel resolution using Erdas Imagine software (Leica Geosystems). For South America, we also created an additional subset for the Caatinga ecoregion from the imagery and ancillary data. The Normalized Difference Vegetation Index (NDVI), available from the MODIS Vegetation Indices products, was added to the dataset as variable for the classification.

For image classification, we chose a supervised decision tree classification approach due to its advantages over other classification algorithms and its capabilities of achieving higher mapping accuracy (Friedl et al. 1999, Friedl et al. 2002, Hansen et al. 2000, Giri & Jenkins, 2005). We performed an extraction of tropical dry forest and non-forest spectral and topographic signatures based on imagery and ancillary data using the NLCD Mapping tool for Erdas Imagine (made freely available by the Multi-Resolution Land Characteristics Consortium through the http://www.mrlc.gov website) and translated the results into the data mining / machine learning software See5 (Rulequest Research, 2008). The See5 software runs a non-parametric algorithm on the training data that relies on hierarchical classifiers to predict class membership by recursively partitioning the dataset into homogeneous subsets based on the reduction of deviance (Giri & Jenkins, 2005). The output from See5 was a decision tree or ruleset that we subsequently applied to acquired imagery data in order to categorize the imagery in land cover classes using the NLCD mapping tool.

We developed and applied three independent decision trees for the North & Central America, South America and Caribbean Islands subregions, respectively. We found that MODIS-Terra surface reflectance daily L2G Global data (pre-processed with cloud cover masking) gave the best results for North and Central America, while the use of MODIS-Terra surface reflectance 8-Day L3 Global composites data improved the results for South America continental coastlines and Caribbean islands by avoiding the recurrent salt-and-pepper effects from cloud cover over in daily surface reflectance data.

Post-classification processing

We evaluated the resultant map of tropical dry forest reserves using a country by country crosscheck for inconsistencies (areas of obvious misclassification) using MODIS imagery and ancillary data. Where needed, we performed a manual recoding of misclassified pixels using Erdas Imagine. Additionally, for the final map, we chose a minimum mapping unit of 100-ha (1-km^2) as a conservative threshold in order to avoid including small isolated pixels arisen due to artifacts of the classification method and the quality of the imagery and ancillary data.

Validation

We collected 1144 points representing tropical dry forests and non-forest sites by interpretation of Landsat imagery collected over Mexico, Venezuela, Bolivia and Brazil. The areas selected for the validation included tropical dry forest landscapes with combinations of large continuous and highly fragmented tracts of forests. The selection was carried out by overlaying a 1-km x 1-km grid over each Landsat scene and generating points randomly within cells that consisted of 100% forest and/or 100% non-forest coverage. This approach was applied in order to reduce the probability of errors typically derived from comparing coarse-scale resolution data to higher-resolution data (Foody et al. 2002). Finally, we constructed an error or confusion matrix by comparing the tropical dry forest final map to the validation points (Congalton, 1991; Stehman & Czaplewski 1998; Foody et al. 2002). The result allowed us to estimate the overall accuracy of the map. We also calculated the Tau coefficient of agreement as a measurement of accuracy of the map in order to compensate for chance agreement (Ma & Redmond, 1995; Naesset, 1996).

Statistics on forest extent, loss, fragmentation and protection

The resultant dry forest map allowed us to extract basic statistics on the total area of tropical dry forest detected at continental, sub-continental and national levels. We considered the results obtained within the “tropical and subtropical dry forest” biome boundaries as representative of the current extent of Neotropical dry forest, while the results obtained within other biome boundaries were considered deciduous vegetation areas with potential for tropical dry forest species distribution and were labeled “Other Deciduous Forests” (ODF). We carried out an assessment on the degree of fragmentation of the tropical dry forests at the continental, sub-continental and national levels. This was made possible by quantifying the percentage of tropical dry forests that occurred in small size forest fragments (<2.5 km^2), intermediate size forest fragments ($\geq$ 2.5 km^2 and $\leq$10 km^2), and large forest fragments ($\geq$10 km^2). This categorization is based on previous work that have suggested that a minimum habitat fragment size of $\geq$10 km^2 is needed to capture the majority of species and processes vital for maintaining ecosystems, and that fragments $\leq$10 km^2 have a higher probability of being converted to other land covers (Rodriguez et al. 2007). Additionally, we performed an evaluation of the tropical dry forest area under protected status, evaluated at the continental, sub-continental and national level. The assessment was achieved by overlaying the resultant tropical dry forest map with the IUCN World Database on Protected Areas (World Conservation Union, 2006) using ArcGIS software (developed by Environmental Systems Research Institute - ESRI).

RESULTS & DISCUSSION

The analysis allowed us to derive a land cover map of tropical dry forest showing the current extent and distribution in the Americas (Fig.3-1). It shows the geographical distribution of tropical dry forests within the “tropical & subtropical dry broadleaf forest” biome (Olson et al. 2001) and the distribution of deciduous vegetation within the Cerrado ecoregion, the caatinga shrubland ecoregion, Dry Chaco ecoregion and the Llanos savanna, Beni savanna and Campos Rupestres savanna ecoregions, based on a supervised classification of dry season MODIS surface reflectance data at 500-m spatial resolution.

During the visual inspection of the map, we found good spatial coherence between ancillary data (Landsat scenes), vegetation indices and the distribution of the dry forests at the country-level, though in highly fragmented areas the extent of small fragments seems to be overestimated. This overestimation is due to the effects of spatial resolution of MODIS, which detects the presence of tropical dry forest only at a minimum mapping unit of 0.25 ha (500-m pixel size), even if the forest patch size is smaller than the pixel itself. Nonetheless, the map was evaluated using a confusion matrix and showed a high overall accuracy of 82% and a Tau coefficient that indicated a spatial agreement of 76% between the map and the ancillary data for all land cover classes (forest/non-forest).

Tropical dry forest extent

According to this analysis, the total extent of tropical dry forest in the Americas is 519,597 km^2. North and Central American dry forests occupy 203,884 km^2 of land, which represents 39% of the total extent of all tropical dry forests, while South America contains 268,875 km^2 of dry forest, which represents 51% of the total. The Caribbean islands comprise 46,839 km^2, which represents 9% of the tropical dry forest remaining. As shown by the map (Fig. 3-1), dry forests are far from being uniformly distributed through the continent. In continental lands, Mexico has the largest amount of tropical dry forest within its boundaries, comprising 38% of all tropical dry forests (Fig. 3-2). Bolivia and Brazil also harbors large portions of dry forest (25% and 17%, respectively), and are followed by Colombia and Venezuela with lower percentages (6.5% and 6.2% respectively). Together, these five countries contain 93% of the tropical dry forests in continental areas.

In the Caribbean islands, the majority of dry forests (92%) occur within Cuba and Dominican Republic (Fig. 3-2). Cuba contains 79% (36,996 km^2) of all Caribbean Islands dry forests representing 7 % of the tropical dry forests in the Americas.

By analyzing trends by ecoregion (Table 3-2 and Table 3-3**),** we found that five single ecoregions (from a total of 28) account for more than half of the tropical dry forests in the Americas (continental and insular) and these ecoregions are: the Chiquitano dry forests (27.5%), the Atlantic dry forests (10.2%), the Sinaloan dry forests (9.7 %), the Cuban dry forests (7.1%) and the Bajio dry forests (7%). The Chiquitano dry forests alone contain 142,941 km^2 of dry forests.

Regarding the extent of deciduous vegetation in savannas and shrubland ecosystems, e.g. other deciduous forests (ODF), the analysis showed that the Dry Chaco comprises 442,667 km^2 of forests, which represent 41% of the estimated 1,069,692 km^2 total ODF (Fig. 2). The Caatinga and Cerrado both have very similar extent of forest vegetation (237,043 km^2 and 234,274 km^2, respectively), each of them representing 22%

of total ODF. The Llanos and Beni savannas are mostly represented by gallery forests and submontane forests encompassing 103,466 km^2 and 43,549 km^2 correspondingly. The Campos Rupestres savannas contain 8,689 km^2 of forest representing 1% of the total ODF. The total extent of ODF is 1,069, 691 km^2.

Tropical dry forest loss

Approximately 48.5% of the tropical dry forest has been already converted to other land uses at the global level (Hoekstra et al. 2005). By comparing the current extent of tropical dry forests in the Americas to its potential extent according to the delineation of the dry forest biome, we found that 66% of the ecosystem has been already converted to other land uses. In North and Central America, 72% of dry forest has disappeared, while South America has lost 60% of its extent (Table 3-1c). The Caribbean Islands region has lost 66% of its extent. Results by country show the high degree of disturbance that has affected the tropical dry forest ecosystem in almost all countries, where the percent lost reaches to 86% in Guatemala and 95% in Peru (Table 3-1a, 3-1b). The analysis was not applied to shrubland and savannas ecosystems since these are generally conformed of a heterogeneous mosaic of vegetation types and there is no estimate for potential forest extent within these areas.

Fragmentation

One of the principal consequences of deforestation is the creation of landscapes occupied by forest fragments that are remnants of original continuous forest cover (Laurance & Bierregard 1997). These fragments are usually embedded in matrices of transformed habitats and can support important biodiversity. Species richness is positively correlated with fragment size, hence, intact large tracts of continuous forest contain a higher number of species per unit area than do smaller forest fragments (Laurance et al. 2002). Since tropical dry forests occur in disjunct patches scattered throughout the Neotropics (Pennington et al. 2006), the land cover map of tropical dry forests at the continental level allow us to further explore the proportion of forest that occurs in smaller fragments ($\leq$2.5 km^2), intermediate size fragments ($\geq$2.5 km^2 and $\leq$10 km^2) and larger forest fragments ($\geq$10 km^2). Larger fragments capture the majority of species and processes vital for maintaining ecosystems functions, while critical size fragments (intermediate and smaller fragments) have higher species extinction rates and probability of being converted to other land covers (Laurance et al. 2002, Rodriguez et al. 2007).

Bolivia contains the highest proportion of dry forests in large fragments across the continent, followed by Brazil and Mexico (Fig. 3-3). It is important to note that in almost all countries, the proportion of dry forests in larger fragments is $\geq$ 60%. This pattern might be due to the way deforestation advances, fragmenting lowland forests and leaving areas of more difficult access and gallery forests intact. Though this pattern of deforestation has reduced a large part of dry forest biodiversity, it can also translate into opportunities for the design of nature reserves and corridors of remaining forests. The highest proportion of critical size fragments is found in countries like Nicaragua, Guatemala, Ecuador, Costa Rica and Peru, which are also low in dry forest extent compared to other countries. Because of the combined effects of their reduced general extent and increased fragmentation, tropical dry forests in these countries have a higher risk of experiencing pressure from human disturbance.

Most countries among the Caribbean Islands have a very high proportion of dry forests in larger fragments (~ ≥80%) except for Jamaica, which has a contrasting higher proportion of critical size fragments (Fig. 3-3). Regarding deciduous forests in savannas and shrublands ecosystems (ODF), the results show that the Dry Chaco consists almost in its totality of large forest fragments. The map also indicates that the Dry Chaco remains as continuous and almost uninterrupted land cover (Fig. 3-3). Caatinga ecosystems are more scattered and fragmented, though an important proportion of larger fragments still survive. The aforementioned pattern is found across the Cerrado, Beni savanna, the Llanos and the Campo rupestres savanna ecosystems, although this pattern is mostly related to soil fertility and moisture gradients (Fajardo et al. 2005, Pennington et al. 2000, 2006) rather than pressure from human activities.

Protected Areas

The results showed that 23,417 km^2 of tropical dry forests are protected by nature reserves in the Americas representing 4.5 % of the total extent (Table 3-1). However, there are contrasting patterns in the degree of protection among all countries (Fig. 3-4). In South America, 17,816 km^2 of dry forests are protected (6.6 % of the total extent). Two countries, Bolivia and Brazil, are jointly responsible for the protection of roughly 64% of all tropical dry forests, with nature reserves that cover approximately 15,000 km^2 of forest. In fact, Bolivia protects 10,609 km^2 of dry forests. Approximately 7,600 km^2 are located within the Chiquitano Dry Forest ecoregion and protected by a single park: the Noel Kempff Mercado National Park.

In North and Central America, where 72% of the dry forests have already been converted to urban or agricultural uses, only 804 km^2 (0.4%) of tropical dry forest benefit from any level of protection. Most of the protection occurs in Mexico and Costa Rica where a similar extent is under protection in both countries (~ 300 km^2). However, the proportion protected relative to their current dry forest extents indicates differences in the relative importance that countries give to the protection of their dry forests. These two countries have large differences in potential and current extent of tropical dry forests, yet Costa Rica protects 15% of its current extent, while Mexico protects only a 0.2 % of its extent. Costa Rica has the highest degree of protection of dry forest in North and Central America, and this might be related to the priority placed on conservation due to income from ecotourism-related activities. This interpretation is supported by results found in the Caribbean islands where, for example, Cuba shows protected areas covering 4,023 km^2 representing 10.9% of its forest extent. Jamaica protects 400 km^2 of forest area, and this amount represents 25% of the country's dry forest extent. In general, countries in the Caribbean Islands show the highest coverage of dry forests under protected status (10.2% of current extent is protected) and countries of North, Central and South America protect 3.9% of the forests' extent. However, protection to forests differs qualitatively given that in North, Central and South America, ~ 90% of dry forests are protected under the

"National Park" status (IUCN Protected Area Category II), while in the Caribbean Islands, 66% are protected under "Sustainable Management areas" (IUCN Protected Area Category VI) and 20% under the "National Park" category.

In the shrublands and savanna ecosystems, 35,820 km^2 of forests are under legal protection representing 3.3% of the total ODF extent. The Dry Chaco and the Cerrado woodlands show the largest extent under protection with 13,310 km^2 and 11,635 km^2 protected respectively, followed by the 5,446 km^2 of forests protected in the Llanos ecosystems. The degree of protection is rather similar across ecosystems, though the Llanos and the Campo Rupestres savanna ecoregions have slightly higher degree of protection (Fig.3-4). Approximately 90% of these protected forests exist under the "National Park" status.

CONCLUSIONS

The use of dry season imagery from MODIS data, selected accordingly to latitudinal differences in tropical dry forest leaf phenology, and the application of a decision tree classification approach within predefined dry forest biome boundaries allowed for the assessment of current land cover extent of the tropical dry forests of the Americas at a 500-m spatial resolution. The tropical dry forest was delimited by the "tropical and subtropical dry broadleaf forest" biome (Olson et al. 2001), which shares similar bioclimatic constraints for the potential extent of tropical dry forest proposed by Sanchez-Azofeifa et al. (2005), but the analysis was extended to forests in the shrublands and savanna biome in order to satisfy wider concepts of the dry forest ecosystem (Pennington et al. 2006, Gentry 1995). The extent of tropical dry forest was analyzed at the continental, sub-continental and country level, including fragmentation and legal protection statistics. We also presented results by ecoregions (Olson et al. 2001) within the tropical dry forest biome and the shrublands and savannas biome. The data provided by this analysis can be used and adjusted by ecologists, biogeographers and conservation practitioners to match regional or local analyses of tropical dry forest extent.

Tropical dry forests, within the strict dry forest biome boundaries, extend for 519,597 km^2 in the Americas: 39% occurs in North and Central America, 51% in South America and 9% in the Caribbean islands. Mexico contains 38% of the tropical dry forests' extent, and correspondingly presented a higher number of different dry forests ecoregions than any other country. Nonetheless, Mexican dry forests have one of the lowest degrees of protection in the Americas. Following are Bolivia and Brazil with a wider extent and proportion of large fragments (>10 km^2) and a larger extent of dry forest under legal protection (17,816 km^2). Most countries have >60% of their dry forests in larger fragments, however, low extent and high fragmentation in countries like Guatemala, Nicaragua, Ecuador, Costa Rica and Peru place dry forests in these countries at higher risk of human disturbance. Countries in the Caribbean Islands have greater legal protection coverage for the dry forests than do continental counterparts, arguably because forest conservation has an economically favorable effect on ecotourism development and watershed protection. Forests in shrubland and savanna ecosystems extend for 1,069,692 km^2, with larger areas occurring in the Dry Chaco, Caatinga, Cerrado and Llanos ecoregions. It is important to note that deciduous forest formations have been reported to occur in smaller valleys and foothills as a result of localized topography, soil and climate variations as these biomes range from humid to dry. These tracts are not included in the calculations of dry forest, shrubland or savanna biome classification from Olson et al. (2001). Since we constrained the analysis to evaluate only regions where dry forest bioclimatic characteristics predominate, we suggest that the scientific community provide supplementary land cover assessments of these localized occurrences using higher resolution imagery, especially if these areas have a high number of endemic species.

We also found that 66% of dry forests have already been converted to other land uses. Dry forests have historically been the preferred zones for agriculture and human settlement in the Americas (Sanchez-Azofeifa et al. 2005, Pennington et al. 2007, Ewel, 1999). North, Central and South American dry forests have suffered intense transformations from agricultural development and cattle ranching, while in the Caribbean Islands, transformations have been driven mainly for urban expansion, tourism development and agriculture (World Wildlife Fund, 2001). The high degree of historical contraction of the extent of tropical dry forests found in this analysis supports the urgency that the scientific community has emphasized in the last decades. The drivers of dry forest conversion should be, however, further analyzed by country, not only because of the large differences in policies for dry forest conservation in the seventeen cited countries, but also because of the broad range of ecological and physical characteristics that can limit or facilitate human use and accessibility to dry forests. Such information can help identify and promote potential sustainable practices through social, agricultural and environmental policies implemented at various levels of decision-making (international, national, provincial, etc).

Even though tropical dry forests evidently play an historical direct role in sustaining human livelihoods, efforts from non-governmental organizations (NGOs) and national institutions remain sporadic regarding the promotion of actions toward the protection and sustainable management of tropical dry forests. Most organizations focus primarily on the protection of humid forest habitats and species (Sanchez-Azofeifa et al. 2005). Globally, approximately 16-18% of tropical humid forests, grasslands and savannas are protected (Hoekstra et al., 2005), a much higher percentage than the 4.5% protection rate for Neotropical dry forests. Tropical humid forests have generally high levels of alpha diversity, perhaps justifying greater protection efforts, particularly in comparison to other ecosystems (Lopez & Zambrana-Torrelio 2006). However, it is important to emphasize that higher biodiversity areas should not always mean higher social and financial investment priorities (Fajardo et al. 2005; Rodriguez et al. 2007). Tropical dry forests not only maintain high levels of species diversity and endemicity but also hold important links to human development in developing countries of Latin America, where its conservation is essential for securing freshwater availability, protecting fertile soils from erosion, and allowing poor communities to benefit from alternative sources of income (e.g. ecotourism; payments for environmental services).

Furthermore, in the neotropics, the deforestation frontier occurs mostly along valleys and foothills of human-dominated dry forest landscapes. Promoting the creation of new protected areas and ecological corridors within fragmented dry forest landscapes, and engaging local communities in sustainable dry forest management initiatives should be more seriously considered as a high priority measure for the mitigation of overall tropical deforestation.

TABLE LEGENDS

TABLE 3-1. Current tropical dry forest extent (km^2) derived from MODIS 500-m data and

area under protected areas at three levels: a) North, Central and South American countries; b) Countries of the Caribbean islands, c) Summary of results per subregion.

TABLE 3-2. Current tropical dry forest extent (km^2) derived from MODIS 500-m data within the dry forest ecoregions of North, Central and South American countries*.

TABLE 3-3. Current tropical dry forest extent (km^2) derived from MODIS 500-m data within the dry forest ecoregions of the Caribbean islands.

FIGURE LEGENDS

FIGURE 3-1. Land cover map showing the extent and geographical distribution of tropical dry forests in the Americas derived from MODIS 500-m.

FIGURE 3-2. Extent (km^2) and percentage of tropical dry forest within the tropical and subtropical dry broadleaf forest biome for countries in North, Central, South America, the Caribbean islands and within shrubland & savannas ecosystems.

FIGURE 3-3. Percentage of tropical dry forest under three levels of fragmentation within the tropical and subtropical dry broadleaf forest biome for countries in North, Central, South America, the Caribbean islands and within shrubland & savannas ecosystems.

FIGURE 3-4. Percentage of tropical dry forest under Protected Areas (IUCN 2006) within the tropical and subtropical dry broadleaf forest biome for countries in North, Central, South America, the Caribbean islands and within shrubland & savannas ecosystems.

(Table 3-1)
a)

Country	TDF Potential Extent (based on Olson et al. 2001)	TDF current extent (this analysis)	TDF converted (%)	TDF Protected (km^2)	Percentage under protection
Mexico	625,038	181,461	71	336	0.2
Bolivia	216,031	118,940	45	10,609	8.9
Brazil	168,164	81,046	52	5,015	6.2
Venezuela	113,143	29,396	74	302	1.0
Colombia	92,664	30,713	67	1,555	5.1
Peru	48,914	2,337	95	188	8.1
Nicaragua	32,277	7,414	77	-	-
Honduras	26,582	6,280	76	-	-
Ecuador	25,275	6,443	75	147	2.3
El Salvador	11,291	3,344	70	9	0.3
Guatemala	10,431	1,463	86	-	-
Costa Rica	7,559	1,795	76	279	15.6
Panama	6,160	2,128	65	-	-
Total	1,383,529	472,759	66	18,620	3.9

b)

Subregion	TDF Potential Extent	TDF current extent (km^2)	TDF converted (%)	TDF Protected (km^2)	Percentage under protection
N & C America	719,338	203,884	72	624	0.3
South America	664,191	268,875	60	17,816	6.6
C. Islands	137,130	46,839	66	4,797	10.2
Total	1,520,659	519,597	66	23,417	4.5

c)

Country	TDF Potential Extent	TDF current extent (km^2)	TDF converted (%)	TDF Protected (km^2)	Percentage under protection
Cuba	109,879	36,996	66	4,023	10.9
Dominican	14,669	6,194	58	368	6.0
Haiti	8,971	2,002	78	0	0
Jamaica	3,438	1,585	54	400	25
Cayman Islands	173	63	64	3.5	5.6
Total	137,130	46,839	66	4,797	10.2

TABLE 3-2. Current tropical dry forest extent (km^2) derived from MODIS 500-m data within the dry forest ecoregions of North, Central and South American countries*.

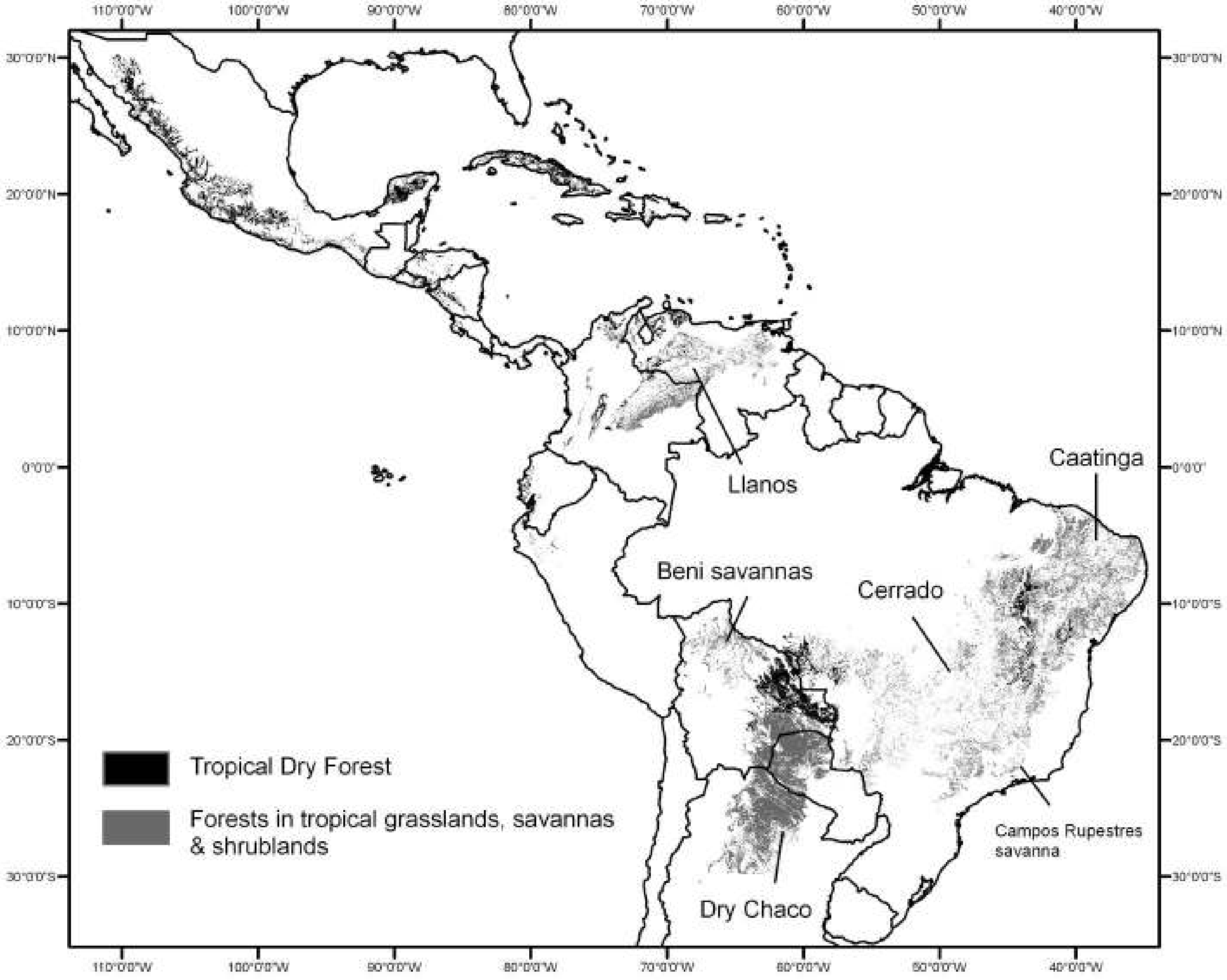
Ecoregions (Olson et al. 2001)	BOL	BRA	COL	CR	ECU	SAL	GUA	HON	MEX	NIC	PAN	PER	VEN	Total	% of Total TDF in America
Bolivian Montane Forests	4,010													4,010	0.77
Chiquitano Dry Forests	114,930	28,011												142,941	27.51
Atlantic Dry Forests		53,036												53,036	10.21
Apure-Villavicencio dry forests			8,484										10,926	19,411	3.74
Cauca Valley dry forests			1,977											1,977	0.38
Magdalena Valley dry forests			9,057											9,057	1.74
Patía Valley dry forests			1,251											1,251	0.24
Sinú Valley dry forests			9,945											9,945	1.91
Central American dry forests				1,795		3,344	1,245	6,280	495	7,414				20,573	3.96
Ecuadorian dry forests					5,549									5,549	1.07
Tumbes-Piura dry forests					894.8							1,497		2,392	0.46
Chiapas Depression dry forests							217.5		2,556					2,774	0.53
Bajío dry forests									14,455					14,455	2.78
Balsas dry forests									36,416					36,416	7.01
Jalisco dry forests									14,867					14,867	2.86
Sierra de la Laguna dry forests									2,563					2,563	0.49
Sinaloan dry forests									50,568					50,568	9.73
Sonoran-Sinaloan transition subtropical dry forest									19,337					19,337	3.72
Southern Pacific dry forests									12,128					12,128	2.33
Veracruz dry forests									926					926	0.18
Yucatán dry forests									27,151					27,151	5.23
Panamanian dry forests											2,128			2,128	0.41
Marañón dry forests												839.5		840	0.16
Lara-Falcón dry forests													8,597	8,597	1.65
Maracaibo dry forests													9,873	9,873	1.90
Total Country	118,940	81,046	3,0713	1,795	6,443	3,344	1,462	6,279	181,461	7,414	2,128	2,337	29,396	472,759	91

*BOL: Bolivia, BRA: Brazil, COL: Colombia, CR: Costa Rica, ECU: Ecuador, SAL: El Salvador, GUA: Guatemala, HON: Honduras, MEX: Mexico, NIC: Nicaragua, PAN: Panama, PER: Peru, VEN: Venezuela.

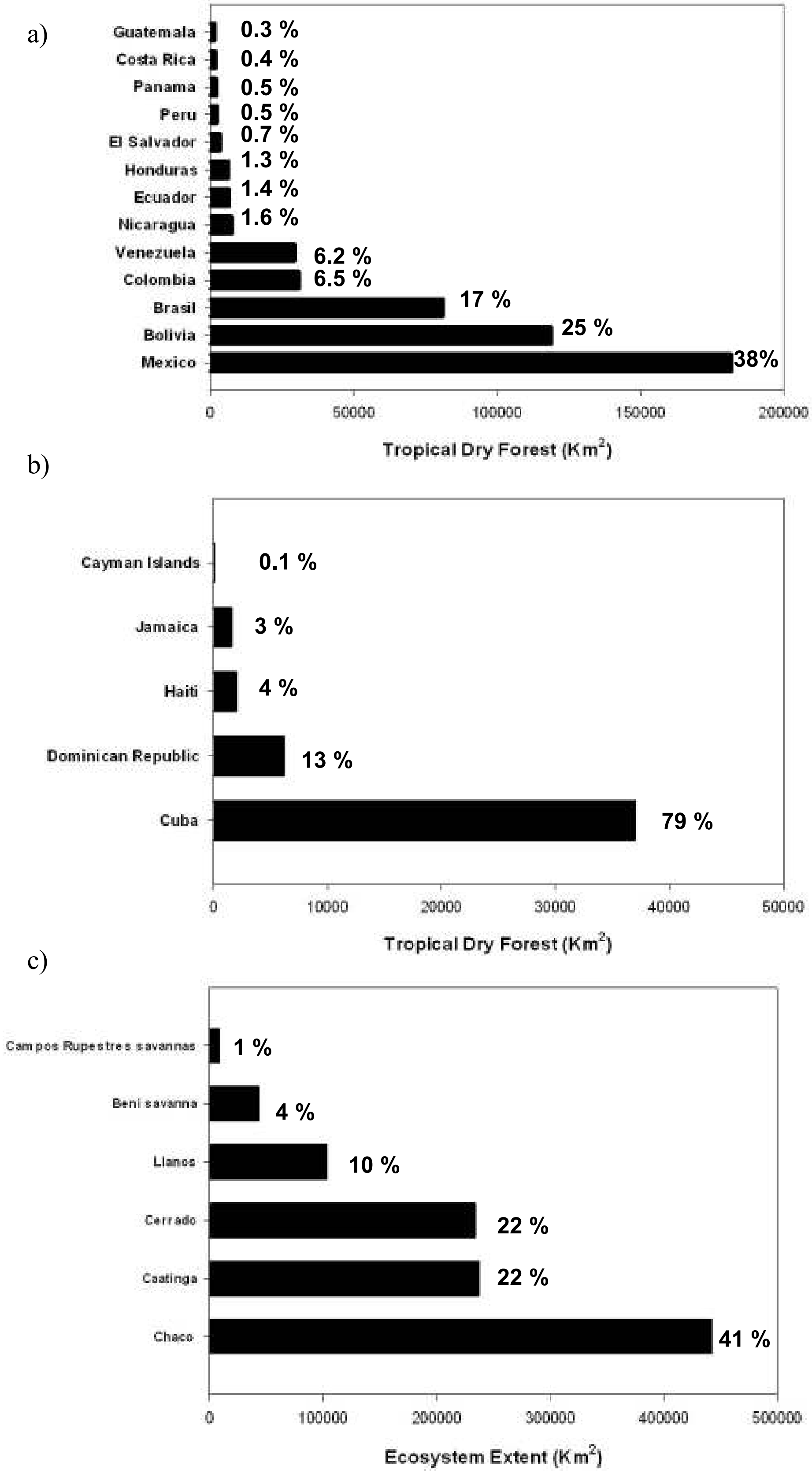
TABLE 3-3. Current tropical dry forest extent (km^2) derived from MODIS 500-m data within the dry forest ecoregions of the Caribbean islands.

Ecoregions (Olson et al. 2001)	Cayman Islands	Cuba	Dominican Republic	Haiti	Jamaica	***Total***	% of Total TDF in America
Cuban Dry forests	63	36,996				37,058	7.1
Hispaniolan dry forests			6,194	2,002		8,196	1.6
Jamaican dry forests					1,585	1,585	0.3
Total Country	63	36,996	6,194	2,002	1,585	46,839	9

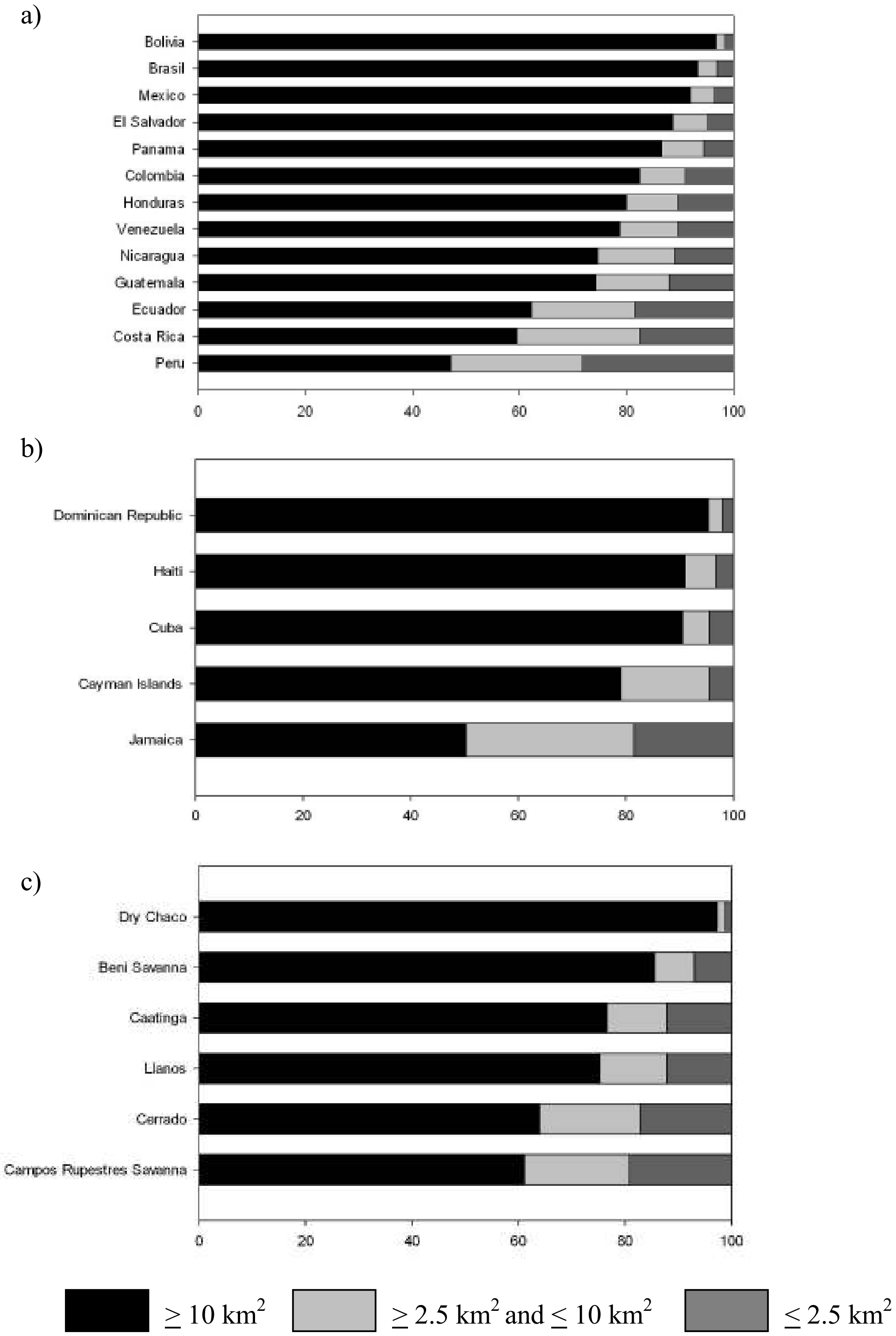
(Figure 3-1)


110°0'0"W
100°0'0"W
90°0'0"W
80°0'0"W
70°0'0"W
60°0'0"W
50°0'0"W
40°0'0"W
30°0'0"N
20°0'0"N
10°0'0"N
0°0'0"
10°0'0"S
20°0'0"S
30°0'0"S
Llanos
Caatinga
Beni savannas
Cerrado
Tropical Dry Forest
Forests in tropical grasslands, savannas & shrublands
Campos Rupestres savanna
Dry Chaco

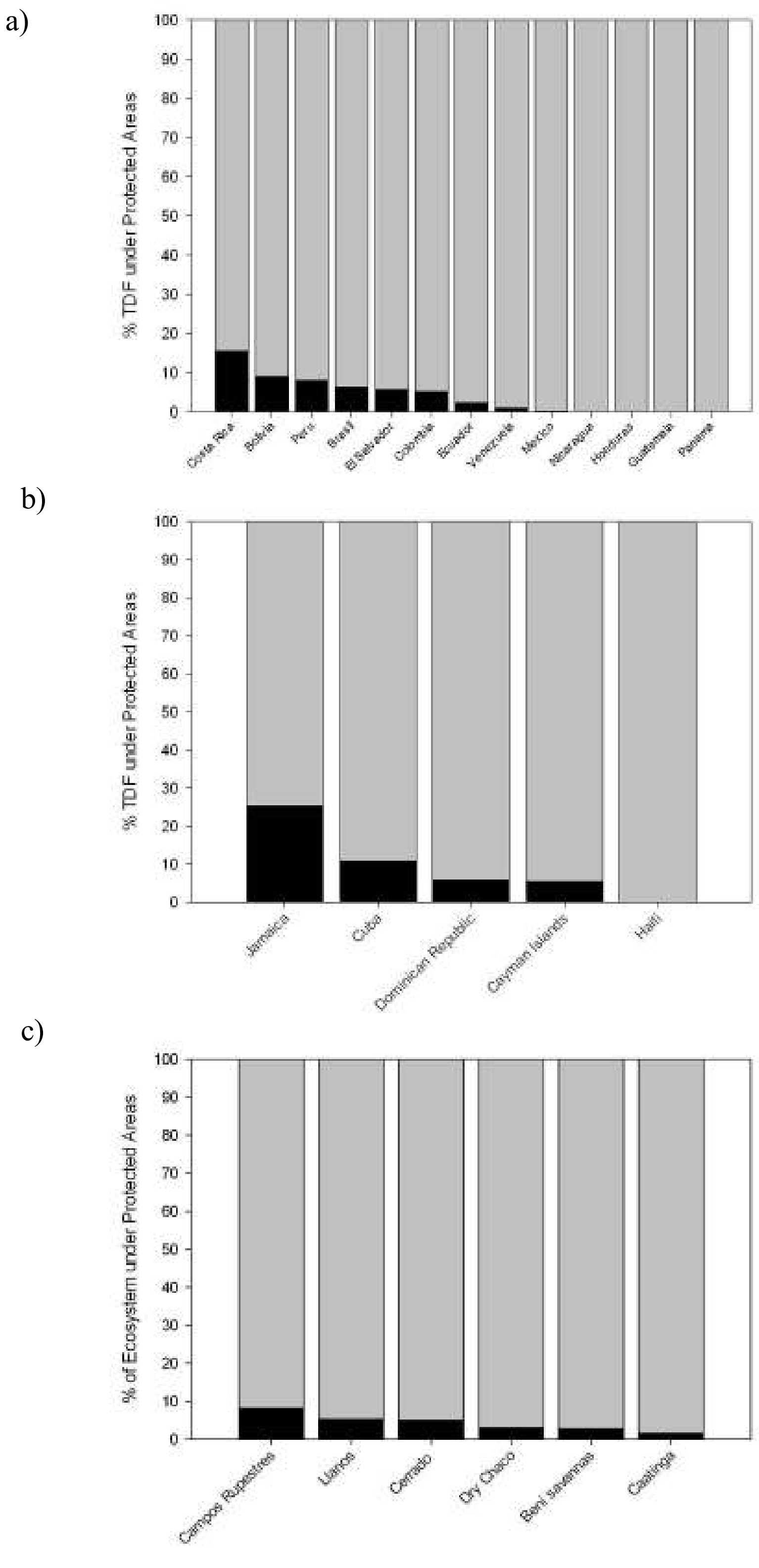
(Figure 3-2)


a)
Guatemala
Costa Rica
Panama
Peru
El Salvador
Honduras
Ecuador
Nicaragua
Venezuela
Colombia
Brasil
Bolivia
Mexico
0.3 %
0.4 %
0.5 %
0.5 %
0.7 %
1.3 %
1.4 %
1.6 %
6.2 %
6.5 %
17 %
25 %
38%
0
50000
100000
150000
200000
Tropical Dry Forest (Km^2)
b)
Cayman Islands
Jamaica
Haiti
Dominican Republic
Cuba
0.1 %
3 %
4 %
13 %
79 %
0
10000
20000
30000
40000
50000
Tropical Dry Forest (Km^2)
c)
Campos Rupestres savannas
Beni savanna
Llanos
Cerrado
Caatinga
Chaco
1 %
4 %
10 %
22 %
22 %
41 %
0
100000
200000
300000
400000
500000
Ecosystem Extent (Km^2)

(Figure 3-3)


a)
Bolivia
Brasil
Mexico
El Salvador
Panama
Colombia
Honduras
Venezuela
Nicaragua
Guatemala
Ecuador
Costa Rica
Peru
0
20
40
60
80
100
b)
Dominican Republic
Haiti
Cuba
Cayman Islands
Jamaica
0
20
40
60
80
100
c)
Dry Chaco
Beni Savanna
Caatinga
Llanos
Cerrado
Campos Rupestres Savanna
0
20
40
60
80
100
■ ≥ 10 km²
□ ≥ 2.5 km² and ≤ 10 km²
▨ ≤ 2.5 km²

(Figure 3-4)


a)
% TDF under Protected Areas
100
90
80
70
60
50
40
30
20
10
0
Costa Rica
Bolivia
Peru
Brasil
El Salvador
Colombia
Ecuador
Venezuela
Mexico
Nicaragua
Honduras
Guatemala
Panama
b)
% TDF under Protected Areas
100
90
80
70
60
50
40
30
20
10
0
Jamaica
Cuba
Dominican Republic
Cayman Islands
Haiti
c)
% of Ecosystem under Protected Areas
100
90
80
70
60
50
40
30
20
10
0
Campos Rupestres
Llanos
Cerrado
Dry Chaco
Beni savannas
Caatinga

LITERATURE CITED

Arroyo-Mora J.P., G.A Sánchez-Azofeifa, M. Kalácska and B. Rivard. 2005. Secondary forest detection in a Neotropical dry forest using Landsat 7 ETM+ imagery. Biotropica. 37 (4): 497-507

Beyer, H. L. 2004. Hawth's Analysis Tools for ArcGIS. Available at http:// www. spatialecology.com/htools.

Castro, K., G.A. Sánchez-Azofeifa and B. Rivard. 2003. Monitoring secondary tropical forest using space-borne data: implications for Central America. International Journal of Remote Sensing. 24(9): 1853-1894.

Congalton, R. 1991. A review of assessing the accuracy of classification of remotely sensed data. Remote Sens. Environ. 37:35-46

Eva, H D., A.S. Belward; E.E. De Miranda; C.M. Di Bella, V. Gond.; O. Huber, S. Jones, M. Sgrenzaroli; S. Fritz. 2004. A land cover map of South America. Global Change Biology 10 (5), 731-744.

Ewel, J.J. 1999. Natural systems as models for the design of sustainable systems of land use. Agroforestry Systems 45: 1–21, 1999.

Fajardo, L., V. González, J. Nassar, P. Lacabana, C. Portillo Q., F. Carrasquel, & J.P. Rodríguez. 2005. Tropical Dry Forests of Venezuela: Characterization and Current Conservation Status. Biotropica 37 (4), 531-546.

Friedl, M.A, C.A. Brodley and A.H. Strahler. 1999. Maximizing Land Cover Classification Accuracies Produced by Decision Trees at Continental to Global Scales. IEEE Transactions on Geosciences and Remote Sensing. Vol 37, No. 2.

Friedl, M.A., McIver, D.K., Hodges, J.C.F., Zhang, X.Y., Muchoney, D., Strahler, A.H., Woodcock, C.E., Gopal, S., Schneider, A., Cooper, A., Baccini, A., Gao, F., Schaaf , C. 2002. Global land cover mapping from MODIS: algorithms and early results. Remote Sensing of Environment 83 287–302

Foody, G. 2002. Status of land cover classification accuracy assessment. Remote Sensing of Environment 80:185-201.

Gasparri, N.I. and Grau, R. (In press) Deforestation and fragmentation of Chaco dry forest in NW Argentina (1972-2007). Forest Ecology and Management. (Available online at

Gentry, A. 1995. Diversity and floristic composition of Neotropical dry forests. In S.H. Bullock, H.A. Mooney, and E. Medina, eds, Seasonally dry tropical forests. Pp. 146-194. Cambridge University Press, Cambridge.

Gillespie, T.W. 2005. Predicting woody-plant species richness in tropical dry forests: A case study from south Florida, USA. Ecological Applications 15(1): p. 27-37.

Giri C.; C. Jenkins. 2005. Land cover mapping of Greater Mesoamerica using MODIS data. Can. J. Remote Sensing, Vol 31, No. 4, pp. 274-282.

Hansen, M., R.S. Defries and J.R.G. Townshend. 2000. Global land cover classification at 1km spatial resolution using a classification tree approach. International Journal of Remote Sensing (6-7): 1331-1364

Hoekstra, J., T. Boucher, T. Ricketts, and C. Roberts. 2005. Confronting a biome crisis: global disparities of habitat loss and protection. Ecology Letters, (2005) 8: 23–29

Janzen, D. H. 1988. Tropical dry forests. The most endangered major tropical ecosystem. Pages 130-137 in E. O. Wilson, editor, Biodiversity. Washington: National Academy Press.

Justice, C., Hall, D., Salomonson, V.V., Privette, J., Riggs, G., Strahler, A., Lucht, W., Myneni, R.,Knjazihhin, Y., Running, S., Nemani, R., Vermote, E., Townshend, J., Defries, R., Roy, D., Wan, Z.,Huete, A., van Leeuwen, W., Wolfe, R., Giglio, L., Muller, J-P., Lewis, P., & Barnsley, M. 1998. The Moderate Resolution Imaging Spectroradiometer (MODIS): Land Remote Sensing for Global Change Research. IEEE Transactions on Geosciences and Remote Sensing, Vol. 36, No. 4.

Kalacska, M. 2005. Use of remotely sensed data to assess Neotropical dry forest structure and diversity. A thesis submitted to the Faculty of Graduate Studies and Research in partial fulfillment of the requirements for the degree of Doctor of Philosophy. Department of Earth and Atmospheric Sciences. University of Alberta. Edmonton, Alberta.

Kalacska M., G.A. Sanchez-Azofeifa, B. Rivard, T. Caelli, H. Peter White, and J.C. Calvo-Alvarado. 2007. Ecological fingerprinting of ecosystem succession: Estimating secondary tropical dry forest structure and diversity using imaging spectroscopy. 108 (1): 82-96.

Laurance, W. and R. Bierregaard. eds. 1997. Tropical Forest remnants: ecology , management and Conservation of Fragmented communities. The University of Chicago Press, USA. P. 612

Laurance W., T.E. Lovejoy, H.L. Vasconcelos, E.M. Bruna, R. K. Didham, P.C. Stouffer, C. Gascon, R.O. Bierregaard, S. G. Laurance, E. Sampaio. 2002. Ecosystem decay of Amazonian forest fragments: a 22-year investigation. Conserv. Biol. 16: 605–618

Lopez, R.P. and C. Zambrana-Torrelio. 2006. Representation of Andean dry ecoregions in the protected areas of Bolivia: the situation in relation to the new phytogeographical findings. Biodiversity and Conservation 15:2163-2175.

Kier, G., J. Mutke, E. Dinerstein, T. Rickets, W. Kuper, H. Kreft and W. Barthlott. 2005. Global patterns of plant diversity and floristic knowledge. Journal of Biogeography 32, 1107-1116.

Ma, Z. and R. Redmond. 1995. Tau coefficients for accuracy assessment of classification of remote sensing data. Photogram. Eng. Remote Sensing 61:435–439.

Naesset, E. 1996. Conditional tau coefficient for assessment of producer's accuracy of classified remotely sensed data. ISPRS Journal of Photogrammetry & Remote sensing 51:91-98.

Miles, L., A. Newton, R. DeFries, C. Ravilious., I. May, S. Blyth, V. Kapos. and J. Gordon. 2006. A global overview of the conservation status of tropical dry forests. Journal of Biogeography. 33, 491-505

Olson, D. M, E. Dinerstein, E.D. Wikramanayake, N.D. Burgess, G.V.N. Powell, E.C. Underwood, J.A. D'amico, I. Itoua, H.E. Strand, J.C. Morrison, C.J. Loucks, T.F. Allnutt, T.H. Ricketts, Y. Kura, J.F. Lamoreux, W.W.Wettengel, P. Hedao, & K.R. Kassem. 2001. Terrestrial Ecoregions of the World: A New Map of Life on Earth. BioScience 51:933-938

Pennington RT, Prado DA and Pendry C. 2000. Neotropical seasonally dry forests and Quaternary vegetation changes. J. Biogeog. 27: 261-273.

Pennington, T, G. Lewis and J. Ratter. 2006. Neotropical savannas and seasonnally Dry Forests: Plant diversity, Biogeography and Conservation. CRC Press, FL.USA.

Prado, D.E. 1993. What is the Gran Chaco vegetation in South America?. I. A review. Contribution to the study of flora and vegetation of the Chaco. V. Candollea 48(1), 145-172.

Queiroz, L.P. 2006. The Brazilian Caatinga: Phytogeographical Patterns Inferred from Distribution Data of the Leguminosae. In Neotropical savannas and seasonally dry forests: plant biodiversity, biogeography and conservation, ed. RT Pennington, JA Ratter, GP Lewis. Boca Raton, Florida: CRC Press.

Rodríguez, J. P., J. K. Balch, and K. M. Rodríguez-Clark. 2007. Assessing extinction risk in the absence of species-level data: quantitative criteria for terrestrial ecosytems. Biodiversity and Conservation 16 :183–209

Rodríguez, J.P., Taber, A.B., Daszak, P., Sukumar, R., Valladares-Padua, C., Padua, S., Aguirre, L.F., Medellín, R.A., Acosta, M., Aguirre, A.A., Bonacic, C., Bordino, P., Bruschini, J., Buchori, D., González, S., Mathew, T., Méndez, M., Mugica, L., Pacheco, L.F., Dobson, A.P., and Pearl, M. 2007. Globalization of Conservation: A View from the South. Science 317 (5839): 755-756.

Rulequest Research .2008. See5: An Informal Tutorial. Available in Internet in the following website: http://www.rulequest.com/see5-win.html

Sánchez-Azofeifa, G.A. et al. 2005. Research Priorities for Neotropical Dry Forests. Biotropica 37 (4), 477-485.

Stehman R. and R. Czaplewski. 1998. Design and Analysis for Thematic map Accuracy Assessment: Fundamental Principles. Remote sensing of Environment 64:331-344.

Trejo I. and R. Dirzo 2000. Deforestation of seasonally dry tropical forest: a national and local analysis in Mexico. Biological Conservation 94 (2000): 133-142

Tosi Jr. J.A. and R.F. Voertman. 1964. Some environmental factors in the economic development of the tropics. Economic Geography 40: 189–205

Vose, R. S., R.L. Schmoyer, P.M. Steurer, T. C. Peterson, R. Heim, T.R. Karl, and J. Eischeid. 1992. The Global Historical Climatology Network: long-term monthly temperature, precipitation, sea level pressure, and station pressure data. ORNL/CDIAC-53, NDP-041. Carbon Dioxide Information Analysis Center,Oak Ridge National Laboratory, Oak Ridge, Tennessee.

World Conservation Union (IUCN). 2006. 2006 World Database on Protected Areas. The WDPA Consortium. [CD-ROM]

World Wildlife Fund 2001. Tropical & Subtropical Dry Broadleaf Forests Ecoregions Report. Available at: http://www.worldwildlife.org/wildworld/profiles/terrestrial_nt.html

Chapter 4 – MODIS Active Fires and deforestation in tropical dry forest landscapes

INTRODUCTION

There is an international consensus on the threats that tropical forest loss imposes on human well-being. For rural communities living in extreme poverty and highly dependent on agriculture, grazing and hunting for subsistence; the degradation and declining productivity of ecosystems threatens their survival (Millenium Ecosystem Assessment, 2005). Sustainable management practices and expansion of forest reserves in tropical deforestation frontiers are urgently needed in order to reduce these negative trends and its impacts on biodiversity and human development.

Recently, several authors have emphasized the important role of tropical dry forest landscapes in providing environmental services to human settlements across the tropics (Ewel et al 1999; Sanchez-Azofeifa et al., 2005, Fajardo et al. 2005). Due to its bioclimatic and ecological characteristics, tropical dry forests have been highly attractive for human development. Tropical dry forests not only maintain high levels of species diversity and endemism but also hold important links to human development in developing countries, where its conservation is essential for securing freshwater availability, protecting fertile soils from erosion, and allowing poor communities to benefit from alternative sources of income derived from ecotourism (Sanchez-Azofeifa et al., 2005, Fajardo et al. 2005). Tropical dry forests are, however, highly threatened by widespread deforestation (Ruiz et al. 2005, Miles et al. 2006, Portillo & Sanchez, 2010). Hoekstra et al. (2005) indicates that this ecosystem has already been reduced to half of its extent at the global scale, and Portillo & Sanchez-Azofeifa (2010) have estimated that only 44% of all tropical dry forests remain in Latin America on highly fragmented patches. Efforts for identifying deforestation patterns and fronts across the tropics have been historically focused in the humid tropics (Mayaux et al. 2003) and little information exist regarding geographical patterns of tropical dry forest deforestation rates at local, regional and global levels.

As a result, alternative tools such as fire occurrence maps have been proposed as potential indicators of deforestation dynamics across landscapes (Mayaux et al. 2003, Eva et al. 2003, Di Bella et al. 2006). Fire is purposely used to manage agricultural lands, hunting, controlling pests, controlling vegetation regrowth and clearing forest for cropland expansion (Wright et al. 2007, Eva et al. 2003). The main rationale behind this relationship is that if, in a given biome, a positive association is found between land cover change and fires, then satellite observed fire data could serve as a critical input in defining 'hot spots' which require intensive monitoring due to their critical rates of land cover change (Eva et al. 2003). Currently, daily global satellite–detected fires are available to the scientific community and the public in general free of charge. If the relationship is true, this data could be analyzed through a Geographic Information System (GIS) in order to highlight forest areas undergoing rapid change (Mayaux et al. 2003, Eva et al. 2003).

Several studies have previously addressed this possibility and in general, statistically significant positive relationships between fire and land cover change has been found although correlation patterns differ among different biomes and land-use types (Ehrlich et al. 1997; Eva et al. 2000). The most evident and strong positive correlations have been found in tropical humid forests at the landscape scale of analysis (Eva et al. 2000, Eva et al. 2003, Morton et al. 2008, Di Bella et al. 2006). Eva et al. (2003), for example, found a Pearson correlation coefficient of 0.94 (99.5% Significance level, n=18) between satellite detected fires and humid forest cover change.

For tropical dry forests, the highest correlation found is presented by Eva et al. (2003) that demonstrated a Pearson correlation coefficient of 0.35 in the dry forest landscape of Santa Cruz site in Bolivia. This study used a sampling grid of 11 x 11 km to evaluate the relation between fire and land cover change (quantified using fine resolution satellite imagery). Di Bella et al. (2006) analyzed vegetation burning patterns using a 0.5º x 0.5º (approximately 50 x 50 km) sampling grid and showed no association between fire density and biomass burning in the semiarid regions (dry forest and grassland steppes) of South America although fire occurrence in these regions was high. Eva et al. (2000, 2003) suggest that a system for identifying land cover change 'hotspots' using satellite-derived fires can only work in biomes where results show robust relationships such as humid tropical forests regions. Overall, results suggest that such a monitoring system would be less useful for detecting deforestation fronts in tropical dry forest sites given the weak relationships that have been found between satellite-derived fires and deforestation.

However, when tropical dry forests are explored at the landscape level, it becomes evident that this ecosystem is more fragmented than tropical humid forests and is generally embedded in an agricultural matrix were the use of fire is high (Portillo & Sanchez, 2010; Fajardo et al. 2005, Di Bella et al. 2006). Therefore, in this ecosystem, it is necessary to discern between the dry forest / agriculture frontier (where uncontrolled fires can cause deforestation) and the agricultural matrices (where fire is used for land management purposes). It is possible that weak correlations between satellite-detected fires and dry forest conversion are a result of the inclusion of a large number of agricultural fires in the analyses, and this is tied to the use of coarse-resolution sampling grids. To correct for this, a different approach where the spatial resolution of the sampling grid is adjusted to the geographic distribution of the dry forest is needed. This will allow a better identification of dry forest / agriculture frontiers, which can be used to investigate the relationship between satellite-detected fires and deforestation. Based on this premise, we explored the correlation between fire and forest cover change in four tropical dry forest sites of South America, following similar methods from previous studies. We also explored the relationship between fragmentation and fire occurrence in dry forest landscapes.

METHODS

Study sites

This study was conducted at four different sites representing tropical dry forest landscapes in South America (Figure 4-1). These four sites were selected to represent typical examples of the dry forest frontier where fire is used as the main tool for setting the land for agriculture and cattle grazing. The following sites were selected: a) Chamela site : located in the Jalisco Dry Forest ecoregion in the Pacific coast of Mexico; b) Machango site: located within the Maracaibo dry forest ecoregion in north-western Venezuela, c) Santa Cruz site: located within the Chiquitano dry forest ecoregion in eastern Bolivia and; d) Parque estadual da Mata Seca site: located between the Atlantic Dry forests / Caatinga ecoregions in eastern Brazil. The analysis was carried out using MODIS 1-km Active Fires data from the years 2002-2004 and land cover change data for the same period. Land cover change data was obtained from processing Landsat TM/ETM+ imagery (28.5 m pixel resolution) and ASTER imagery (15 m pixel resolution).Table 4-1 shows the type of land use driving deforestation at each of the study sites and the respective satellite imagery used for the analysis. A more detailed description is provided below.

Chamela-Cuixmala Biosphere region, Mexico

The Chamela site covers a portion of approximately 50 km along the coastline of western Jalisco State in Mexico, and 70 km into the mountain range. The site is centered on 105°5’19”W and 19°49’12”N in the vicinity of the Chamela-Cuixmala Biosphere reserve. The predominant vegetation type in this region is lowland deciduous forest, but other habitats include riparian forest, coastal vegetation, mangroves, palm forest and spiny thorn forest (Stoner, 2005). Human settlements have transformed part of the landscape around this area, but a high percentage of mature and successional dry forests is still found in fragments and continuous patches owned by communal organization of peasants - Ejidos - (Sanchez-Azofeifa et al. 2008). Adjacent to the reserve, there are less than 50 human settlements with a population of about 10,000 people carrying productive activities such as cattle ranching and agriculture. During the 1970’s a governmental program for clearing lands and opening them for agricultural activities was implemented at the national level promoting local use of slash and burn land use pattern (Castillo et al. 2005). According to Ellingson et al. (2000), land clearing practices in Mexico’s TDF are similar to slash-and-burn activities conducted throughout the tropics; the forest is cleared, burned and planted to maize and other crops. After harvest, the land is used for cattle ranching, and pasture fires are set every 2-3 years to increase grass production, remove residual dead grass biomass and prevent the establishment of invading shrubs. Development for tourism infrastructure has been reported as an important driver of deforestation in the recent years.

Machango region, Venezuela

The Machango site is located along the eastern coast of Lake Maracaibo, north-western Venezuela. The site's landscape is a mixture of tropical dry forest remnants and small rural communities, centered at 70°39'54"W and 10°26'45"N. The area includes the Machango river basin, an important freshwater source for urban communities and agricultural development on the eastern coast of Lake Maracaibo. Population density in the area is approximately 30 inhabitants per km^2 (Fudeco, 2004). Some of the very few dry forests fragments left of the Maracaibo Dry forest ecoregion exist in this region, an ecosystem that has been reported as a critically endangered ecosystem by Dinerstein et al. (2005). In the region, agricultural activities include the cultivation of sugarcane and coffee crops, however, most of the land is used for cattle ranching. Information on the land use dynamics and deforestation trends is scarce for this site, although the use of fire for clearing the land has been often associated with widespread uncontrolled deforestation events.

Santa Cruz, Bolivia

The Santa Cruz site is located in eastern Bolivia. It is centered at 62°4'35"W and 17°13'25"S. These formations are part of the Chiquitano Dry Forest ecoregion which harbors the largest extent of continuous and undisturbed dry forest in the Americas (Portillo-Quintero et al. 2010). The region, however, undergoes rapid deforestation rates and is considered one of the most endangered forest area in the Neotropics (Steininger et al. 2001a). Land cover and land use dynamics in this region has been extensively documented by previous authors (Killeen et al. 2007; Steininger et al. 2001a; 2001b). Deforestation due to intense development in lowland Bolivia exceeded 1500 km^2/year during the 1980's and 1990's driven by low land prices, infrastructure development and macroeconomic policies designed to promote an export economy based on agriculture (Steininger et al. 2001a). Fire, of both natural and anthropogenic origins, has likely been a pervasive influence on these dry forests (Kennard et al. 2001, Vieira 2006). Although fire is used for clearing and maintaining the land for agricultural purposes (Morton et al. 2008), forest managers have also applied prescribed burning as a silvicultural tool to enhance the regeneration of shade-intolerant tree species (Kennard et al. 2001).

Parque Estadual da Mata Seca, Brazil

The Parque Estadual de Mata Seca site is located in along the border of northern Minas Gerais state and south-western Bahia state in Brazil and centered at 14°28'29.67"S and 43°23'19.43"W. The region is mainly covered by agricultural lands and highly fragmented remnants of tropical dry forest and Caatinga forest within the Atlantic Dry Forest and the Caatinga ecoregion of eastern Brazil. Since the 1970's, authorities have promoted the occupation of this area in the Brazilian semi-arid lands and the conversion of its forests for cattle rising and agriculture production (Alves, 2008). The region includes the Mata Seca State park, which protects one of the last remnants of what it once was a vast extension of tropical dry forests. In the region, the incidence of uncontrolled anthropogenic fire used to manage pastures surrounding forest fragments eventually burns part of the forest (http://tropi-dry.eas.ualberta.ca).

MODIS Active Fires

MODIS Active fires at 1-km^2 resolution from the MODIS sensors on board of the Terra & Aqua satellite platforms were used in this studies. The MODIS active fire algorithm uses a contextual approach that exploits the strong emission of mid-infrared radiation from fires (Giglio et al. 2003). A detected fire represents the center of a pixel flagged as containing one or more actively burning fires even detecting both flaming and smoldering fires much smaller than 1km^2 (Giglio et al. 2003). The MODIS active fire detection algorithm is applied to day and nighttime data from the Aqua and Terra satellites, in order to differentiate surface heating between forest and cleared area in the daylight that might contribute to false detections (Wright et al 2007, Morton et al. 2008). Data from the Collection 3 & 4 of MODIS Level 2 Fire product which includes confidence estimates for fire detections ranging between 0% and 100% was used for this study. These confidence estimates are used to assign one of the three fire classes (low-confidence fire, nominal-confidence fire, or high confidence fire) to all fire pixels within the fire mask (Giglio, 2007). Detection of active fires can also be obscured by clouds, especially during the rainy season in tropical environments. On the contrary, the probability of omitting active fires by the passing of clouds is lower in tropical semi-arid and arid environments. Although MODIS algorithms have included several technical considerations to improve the quality and confidence of fire detections, low confidence fires detected or false alarms are generally included in the datasets provided by the MODIS Rapid Fire response System (http://rapidfire.sci.gsfc.nasa.gov/) to users. Ground truthing the large amount of daily, weekly or monthly fire data that can be collected globally or for a specific region over a period of time could be a time-consuming task for managers and/or researchers interested in translating spatial patterns of anthropogenic fire into decisions for the prevention of deforestation events. Therefore, in this analysis the correlation between all active fires data available for each site and land cover change was evaluated. For each study site, we used MODIS Active Fires detected during the years 2002, 2003 and 2004 including fires detected at all confidence-levels.

The MODIS active fire algorithm can detect a high number of fire detections clustered in a single area on the ground. Previous to the analysis, the pattern of aggregation and the degree of spatial autocorrelation of the MODIS Active Fires using Moran's Index for each fire data collection was evaluated using the Spatial Autocorrelation tool in the ArcGIS software (ESRI, 2008). A Moran's Index value near +1.0 indicates clustering while an index value near -1.0 indicates dispersion. The tool also returns Z-score values evaluating the significance of the index value. If a pattern shows Z-score values outside the range between -1.96 and +1.96, it is classified as statistically significant clustered or statistically significant dispersed (Table 4-2). It is important to notice that clustered active fires do not necessarily represent the occurrence of many different fires, but they can also represent a single severe fire that spread over space (expanding for few kilometers) or over time (lasting for several days and moving across the forested landscape) and therefore, it can be detected by the sensor in adjacent MODIS pixels. The occurrence of spatially autocorrelated active fires (non-independent) in clusters across the landscape can also be an indicator of severity or intensity of an uncontrolled fire. Such clustered patterns could be important as deforestation indicators.

Medium resolution remote sensing information for land cover change mapping.

For each site, areas where conversion from dry forest to any other land use occurred were identified by comparing time-series of two successive high spatial resolution satellite images representing an “initial state” and “final state” of the forest land cover. Imagery acquired from the Advanced Spaceborne Thermal-Emission and Reflection Radiometer (ASTER) and the Landsat TM and ETM+ sensors were used in this study (Jensen, 2007). The ASTER sensor flies on board of the Terra satellite and provides spectral information in the visible and near-infrared spectral bands at 15-m spatial resolution. ASTER imagery was acquired through the Land Processes Distributed Active Archive Center (LPDACC) available online (http://lpdaac.usgs.gov). Landsat data was acquired from the Global Land Cover Facility (http://www.landcover.org) and the Earth Resources Observation Systems (EROS) Data center through the USGS Global Visualization Viewer – GLOVIS – (http://glovis.usgs.gov). Problems associated with the Landsat ETM+ Scan Line Corrector (SLC) caused from a sensor failure on May 31st, 2003 resulted in imagery datasets with significant amount of missing data in the form of stripes (Jensen, 2007). A mask of the missing data (gap mask) is provided with the ETM+ imagery acquired for final state of the time series at the Machango Venezuela site. All satellite time-series images were geo-corrected for pixel-to-pixel co-registration without affecting the original spatial resolution.

Dry season imagery (Table 4-1) was selected for all sites since dry forest structural properties are more pronounced and distinctive during the dry season (Kalacska et al. 2007) allowing tropical dry forest areas to be discerned from semi-deciduous and from evergreen gallery forests within the tropical dry forest matrix. The use of dry season imagery also improves the chances of acquiring cloud-free imagery. No atmospheric correction was applied to the ASTER acquired since our analysis involves further image rationing (transformation to a vegetation index) that reduces many forms of multiplicative noise from atmospheric sources (Jensen, 2007). Acquired Landsat TM and ETM+ products were radiometrically and geometrically corrected (http://eros.usgs.gov).

Land cover change

For the Santa Cruz and the Machango site, the assessment of dry forest cover change was achieved by using a vegetation index differencing technique (Mas, J. 1999). This technique uses data transformation that involves the use of red and infrared bands to produce a dimensionless, radiometric measure that shows the relative abundance of green biomass (Vegetation index) for each scene. In this method, time series of vegetation indices are subtracted to produce a residual image which represents the change in green biomass between the two dates (Mas, J. 1999). Each acquired image was transformed into a Normalized Difference Vegetation Index (NDVI) which is the normalized ratio of the red reflected radiance flux to near-infrared radiant flux. The index was calculated by applying the formula: NDVI= (Near-infrared band –Red band) / (Near-infrared band + Red band).

Once the NDVI time-series were obtained for each site, the change detection module from Erdas Imagine (Leyca Geosystems, 2008) was used to highlight pixels that suffered significant decrease in NDVI values from the initial state to the final state of the time series. Several thresholds were used through iterative comparisons with false color composites (RGB 453) which are able to enhance the contrast between forested and non-forested areas. Specific thresholds of NDVI change successfully identified (-25% for Santa Cruz and -10% for Machango) deforestation events across the landscape. The differences in the selected thresholds could be the result from differences between soil moisture conditions in the dry season of the initial and final of the time series and/or sun illumination differences. The result is an image depicting areas of significant drop in NDVI values caused by deforestation events (deforestation map). Consistency and accuracy of the results was ensured through visual inspection by comparing to the false-color composites of the time series. Manual recoding of misclassified areas was performed where needed. As baseline data for the analysis, I also performed an unsupervised classification (ISODATA) on the images of initial state of the time series in order to produce Forest / Non- Forest maps for the Santa Cruz and Machango sites.

The Vegetation index differencing technique was not able to identify deforestation events in the Mexico site and the Mata Seca site properly and often mistook NDVI changes in crops as deforestation events. For these sites, I an unsupervised classification (ISODATA) on both images of the time series in order to produce Forest / Non- Forest maps for each site was performed. The change detection module from Erdas Imagine (Leyca Geosystems, 2008) was then applied to create a mask showing areas of transition from forest to non-forest in these two sites. Visual inspection and manual recoding of misclassified areas was also performed.

GIS Analysis

The objective in our study was to calculate the spatial correlation between the number of MODIS Active Fires and tropical dry forest cover change. In order to focus our analyses strictly within the tropical dry forest landscape, analyses were made within the limits of the dry forest ecoregion as delineated by Olson et al. (2001) for each site. Following Eva et al. (2000, 2003) and Di Bella et al. (2006), we extracted sample observations from the data using a square grid. For analyses at global scale that include multiple ecosystems, Eva et al. (2000, 2003) used a 11 x 11 km grid to divide the landscape in subsamples or sampling boxes. Human-dominated tropical dry forest landscapes are, however, highly fragmented and contain a great amount of agricultural and cattle grazing lands that are subject to regular burning. To analyze our data, I established a sampling grid size of 3 x 3 km in order to capture the effects of active fires occurring closer or within dry forests. This specific size was selected arbitrarily by observing and comparing results on several grid sizes. The 3 x 3 km sampling grid scheme was found able to record small-scale to large-scale fire use intensity patterns, reducing the inclusion of a large number of different agricultural fire use patterns per box and still obtaining a high number of samples per site. The analyses were performed only for 3 x 3 km sampling boxes that represent the agriculture / dry forest frontier where deforestation takes place. The agriculture/ dry forest frontier was defined following Eva et al. (2000) as areas dominated mainly by forest (>50% of the box).

Using ArcGIS software (ESRI) and Hawth's Tool module for ArcGIS, we extracted the following data for each 3 x 3 km box: a) Number of MODIS Active Fires, b) Percentage of Forest, c) Percentage of pixels representing deforestation events. In order to understand the effect of agricultural fires on the correlation between fire and deforestation, results were analyzed as a function of the proportion of forest within each box (from 50% to 95%, with unit increments of 5%). The relation between dry forest fragmentation (number of forest fragments) and the number of fires.

RESULTS

A summary of the fire distribution patterns for each site is shown in Table 4-2. The Chamela and the Santa Cruz site showed the largest fire densities (0.45 and 0.47 fires/km2 respectively) while the Mata Seca site and the Machango site showed lower fire densities of 0.15 and 0.08 fires/km2, respectively. Even though, the Chamela site showed high fire density across the landscape, the pattern of aggregation was found to be random (Moran´s I=0.11, Z=0.09). Fire occurrence was also randomly distributed for the Machango and Mata Seca site. For Santa Cruz, the pattern of aggregation was found to be clustered. A description of the relationships between MODIS Active Fires and deforestation patterns at each site and the land use driving such relationships follows.

Chamela-Cuixmala Biosphere region, Mexico

Significant correlations between MODIS fires and forest cover change were observed at this site. When using boxes with 50% and 55% of forest cover, we found Pearson correlation coefficients of 0.34 ($p < 0.014$, $n = 49$), and of 0.36 ($p < 0.012$, $n = 45$), respectively. At higher percentages of forest cover (>60%) all correlations were not significant (Table 4-2, Figure 4-2). The site has no clear fire aggregation pattern (Figure 4-3). In general, the use of fire occurs in low numbers and is widespread in the region, even in areas with a high percentage of forest, with no strong forest cover change detected. Deforestation was generally associated to already intervened and accessible areas.

The use of fire in the region is less intensive (pasture fires are set every 2-3 years to allow grass regrowth) mostly related to small-scale farming. In areas with higher percentage of forest, fire occurrence persists in low numbers. There is a possibility these fires are well managed, controlled and restrained to pastures, or that forest cover change is small enough not to be detected in the land cover change analysis using fine resolution imagery. Moreover, no correlation between the percentage of forest cover change and fragmentation patterns was found. Forest cover change associated to fire seems to be restricted to highly fragmented forest landscapes with >50% and <65% forest cover, which is supported by the significant correlation found between MODIS fires and the number of fragments at this site (R=0.24, p < 0.0008, see Figure 4-2).

Machango region, Venezuela

Deforestation is widespread at the Machango site, however, it showed no significant correlation to MODIS fires from the 2002 to 2004 period (Table 4-2, Fig 4-2). Fires were generally found near forest edges although mostly dispersed with no clear aggregation pattern and no relation to fragmented landscapes (Figure 4-3). At this site, land cover transformation is driven by a low population of small farmers, who manage fire and clear smaller tracts of forest for cattle grazing and agriculture. A moderate but significant correlation between forest cover change and fragmentation was found (R=0.46, p < 0.0017, See Figure 4-4). This result indicates that deforestation at this site is favored by increased accessibility to forest edges in fragmented forests.

Santa Cruz, Bolivia

Overall, there was a strong and significant relationship between MODIS fires and land cover change in the Santa Cruz site during the 2001-2005 period (Table 4-2, Figure 4-2). When using boxes with >50% and >70% forest cover, I obtained correlation coefficients ranging from 0.68 to 0.78 (P <0.01). Figure 4-3 shows areas of greater land cover change occurring where MODIS fires are numerous and aggregated in the landscape. Most fires were associated to forest edges and fewer fires were located inside forested areas and/or agricultural lands. The best correlation was found when using boxes with >65% forest cover (R = 0.78, P <0.0003, *n* = 16). When using boxes with >70% forest cover, the correlation was lower and not significant (R = 0.43, P < 0.56, n = 4) and no samples were found with higher percentages of forest cover. Figure 4-4 shows that there was no significant correlation found between forest fragmentation and forest cover change, neither between forest fragmentation and MODIS fires. These results show that the use of fire at the Santa Cruz site is strongly associated to deforestation affecting continuous and fragmented forest landscapes in a similar way.

Parque Estadual da Mata Seca, Brazil

For the Mata Seca site, a moderate but statistically significant correlation between forest cover change and the number of fires detected by MODIS during the 2001-2004 period was found (Table 4-3a, Fig 4-2). Pearson correlation coefficients ranged between 0.39 and 0.54 (P < 0.0001). At this site, even though fires showed a random distribution (see Table 4-1), there was a clear aggregation of fires near forest edges of small and large forest fragments (Fig 4-3). Forest cover change occurred in areas with very high number of fire detections. Many fires were also detected within the forest, although no forest cover change was identified. These might represent small intensity fires that are used to clear the understory for logging activities and cattle grazing, which is a common practice in the region (Vieira, 2006). Although it is clear that large tracts of dry forest are converted through the use of fire in the Mata Seca site, this diverse scheme of land use and forest conversion affects the correlation between fire and forest cover change. Also, our results show that correlations tend to improve in areas with high percentage of forest (Table 4-3, Fig 4-2). The best correlation (R=0.54, P <0.0001, n = 64) was found in boxes that had more than 95% of forest. Evidently, in boxes with >95% forest, there is a high probability that a fire occurrence is associated to a deforestation event. Obtaining significant correlations at the Mata Seca site was possible because the number of samples (*n*) was held high even when restraining the analysis to boxes with >95% forest cover (Table 4-2). Furthermore, no significant correlation between MODIS fires and forest fragmentation (number of fragments) was found. We did found a moderate but significant correlation between the number of fragments and forest cover change (Figure 4-4). At this site, deforestation affected the most fragmented and disturbed forests primarily.

DISCUSSION

In general, our analysis shows that no single overall correlation can be found between the frequency of MODIS Active fires and forest cover change in tropical dry forest landscapes. These relationships can be low, moderate, strong or non-existent depending on the frequency and intensity of the use of fire for forest clearing practices in each site. As our results show, this seems to be related to the type of land uses promoted at each site. The Santa Cruz site showed strong correlations related to fire-intensive large-scale deforestation practices for development in the region. In the other hand, the Mata Seca site and the Chamela site showed moderate significant correlations. Results for the Chamela site correspond to dynamics from small-scale agriculture and logging activities, while results from the Mata Seca site correspond to a mixture of large-scale, small-scale and understory forest clearing practices promoted by the local authorities. In the Machango site, where very small-scale subsistence agriculture predominates, MODIS fires were disperse and occurred in low numbers showing no correlation to deforestation events.

We also found that the correlation between MODIS fires and deforestation in all sites improved when increasing the proportion of forest in each box. As explained before, at each increment the percentage of forest in each box, there is a higher probability that a fire occurrence is associated to a deforestation event. However, the correlation tends to decrease with further increments in the proportion of forest. This occurs due to a decrease in the number of sampling boxes when the threshold for proportion of forest is also incremented. Figure 4-5 shows that sites with low number of samples return more significant relationships when the proportion of forest in each box is >50%. These could be slightly improved by increasing the proportion of forest in each box, however, after reaching >65% forest cover, all correlations decreased at these sites due to very low number of samples. In the Mata Seca site moderate significant relationships were stable regardless of the proportion of forest in each box and this was possible due to the high number of samples for the region. Given the importance of having a significant number of samples to understand the relationship between fire and deforestation, the use of Landsat scenes over ASTER scenes might be preferable given the image dimension of a Landsat scene (185 x 185 km). The use of a Landsat scene can increase the number of samples and improve our probability of finding stable relationships in a large geographic area. However, the extent and geographical configuration of the dry forest, as well as land use type and fire use frequency at each site, are determinant factors on obtaining a significant number of samples at the agricultural / forest frontier. In general, regardless of the type of sensor used to map forest cover change, we found that sampling boxes with >50% - >60% forest cover are able to maintain a considerable number of samples for each site and derive stable correlations between MODIS fires and deforestation (Figure 4-5c).

One other aspect is the effect of fragmentation on fire occurrence and deforestation patterns. Our results do not support the idea that fire occurrence associated to deforestation is generally favored by forest fragmentation (Figure 4-4). We found a moderate and significant correlation between MODIS fires and the degree of forest fragmentation at the Chamela site, but no significant relationship in all other sites. We also found significant correlations between deforestation and fragmentation at the Mata Seca and the Machango site, but none in the Chamela and Santa Cruz site. Although results do not show strong significant relationships, these results show that forest fragmentation favors deforestation in regions where small-scale shifting agriculture exists (Machango, Mata Seca, Chamela). At the Santa Cruz site where regional agricultural and industrial development programs are promoted, results show less predictable deforestation patterns.

In the Santa Cruz site there was clear pattern of fire aggregation (clusters) along forest edges associated to large deforestation events. In the Mata Seca site, there was a also clear aggregation of fires near forest edges of small and large forest fragments.Nevertheless, in order to find ‘hotspots’ of deforestation in a tropical dry forest landscape through the use of satellite-derived fires, visualizing clusters of fires is not enough and might lead to misinterpretations. For example, at the Chamela site, no clear aggregation of fires along deforestation fronts was observed, but we did find a significant correlation between MODIS fires and deforestation in highly fragmented areas (boxes with a minimum of >50% and >60% forest), a pattern that is not clearly evidenced in a fire frequency map. The use of a sampling grid for relating forest cover and fire counts at the agricultural / forest frontier is then necessary in order to identify deforestation fronts in tropical dry forest landscapes.

Finally, it is important to mention that three main methodological aspects might have contributed as sources of error to the analysis. Ideally, we would have analyzed deforestation events that occurred strictly between the initial and final months of the 2002-2004 period, however, in most of the cases cloud-free satellite imagery was not available for these dates. Therefore, acquisition of imagery for the years 2001 and 2005 was necessary in order to include the total accumulation of deforestation events occurred during the 2001-2004 period. The use of a wider time range for the deforestation analysis could have resulted in an overestimation of the transformed area.

Also, the errors in the imagery classification scheme can result in false deforestation events and skewed correlations. Whether change detection is performed using the NDVI differencing method or forest cover maps from unsupervised classifications, the verification of the deforestation maps by visual inspection of time-series in false color composites and corrective methods such as the manual recoding of misclassified areas might be needed in order to improve consistency and accuracy. For tropical dry forests, the use of dry season imagery is preferred, since previous studies have shown that the use of dry season imagery, can improve the discrimination of dry forest from semi-deciduous and from evergreen gallery forests within the tropical dry forest matrix (Kalacska et al. 2007, Portillo-Quintero, 2010).

Furthermore, in this study we arbitrarily chose a sampling box size that would allow to capture the effects of active fires occurring closer or within dry forests. This specific size was selected arbitrarily by observing the representation of the agriculture / dry forest frontier on several grid sizes. We found that a 3 x 3 km sampling grid scheme was able to record small-scale to large-scale fire use intensity patterns, reduce the inclusion of a large number of different agricultural fire use patterns per box and obtain a high number of samples per site. Nonetheless, we suggest that further research should evaluate the effect of several sampling box sizes on the correlations found in tropical dry forest and humid forest landscapes. Such study could shed more light on the influence of the sampling scheme on the differences in correlation between detected fires and deforestation in humid and dry forests.

CONCLUSIONS

Tropical dry forests are the most threatened tropical ecosystem (Sanchez-Azofeifa et al. 2005; Vieira et al. 2006). This ecosystem is strongly associated to important ecosystem services to human populations in the tropics, and its conservation is essential for sustaining the well-being of rural and urban communities. Understanding spatial patterns of land cover change in tropical dry forest landscapes can help us understand where exactly this forest is being lost at a higher pace at the landscape, regional or global level. This information can be used to direct national and regional authorities, NGO's and the scientific community to invest more time and resources in specific areas where dry forest is being converted. Apart from traditional change detection techniques using remote sensing, the use of remotely-sensed fires as a tool to identify deforestation fronts is very promising but it has only been suggested for humid tropical forests (Eva et a. 2003, Di Bella et al. 2006). MODIS Active fires are freely available as GIS files and Google Earth files and can be downloaded daily or weekly for any region in the world (http://rapidfire.sci.gsfc.nasa.gov/). Any institution or NGO can obtain this data and use as an input on their GIS in order to analyze fire occurrence patterns. Yes, it might be interesting to study the effect of the use of different confidence values in the relationships, however, the confidence levels are an output of the Active Fires algorithm which already contains a series of measures to minimize false detections. Thus confidence levels represent fires of low-intensity (but still higher than 310K) to high-intensity (very high temperatures-unambiguous fires). So I think this aspect does not compromise the analysis.

This study shows that satellite-derived fires could be used as predictors of deforestation in tropical dry forest ecosystems, as well. Our findings shows there can be none to low, moderate or strong significant relationships between the MODIS Active fires product and tropical dry forest cover change. This relationship is, however, dependent on the proportion of forest in the sampling boxes and the fire-use intensity of the land uses at each particular site. In general, the use of remotely-sensed fires could be a promising tool for identifying deforestation fronts in tropical dry forest landscapes in a spatially explicit, highly-informative and cost-effective way. In this study, we used MODIS Active Fires detected at all confidence-levels (Giglio et al. 2003). It is important to know that the use of fires at all low confidence values does not compromise the results. Confidence levels are an output of the active fires algorithm which already contains a series of measures to minimize false detections. Confidence levels, in fact, represent fires of low-intensity but still over the minimum threshold (310 K) for fire detection. High confidence levels represent high-intensity fires (very high temperatures-unambiguous fires). However, we think it might be valuable to further study the effect of the use of the different confidence values assigned to MODIS active fires on the correlations.

Establishing a fire-monitoring system to detect deforestation fronts in a tropical dry forest landscape will require a set of MODIS Active fires collected over a period of time (several months or years) and precise ancillary information on forest cover extent and distribution, types of land use and information on how fire is used across the region. Using the method applied in this work would allow setting an a priori confidence level for the monitoring system. A strong and statistically significant correlation over the region of interest is preferred before suggesting potential deforestation ‘hotspots’, but a moderate and statistically significant correlation could also be useful, if it is supported by extensive and precise ancillary information.

TABLE LEGENDS

TABLE 4-1**.** Comparative table showing: a) land use driving deforestation and, b) the satellite imagery used at the initial and final state of the time series; for the Mata Seca, Santa Cruz, Chamela and Machango sites.

TABLE 4-2**.** MODIS Active Fires distribution patterns at each site. The Spatial Autocorrelation (Moran's I) tool in the ArcGIS software (ESRI) was used. A Moran's Index value near +1.0 indicates clustering while an index value near -1.0 indicates dispersion. The tool also returns Z-score values evaluating the significance of the index value. If a pattern shows Z-score values outside the range between -1.96 and +1.96, it is classified as statistically significant clustered or statistically significant dispersed.

TABLE 4-3**.** The Pearson correlation coefficient (*R*) between deforestation and number of MODIS fires in 3 x 3 km sampling grids at four sites in South America. Results are shown as a function of the thresholds used to define the agriculture / forest frontier for each sampling box (% of forest). LS= Level of Significance. *n* = number of samples.

FIGURE LEGENDS

FIGURE 4-1. Location of the sample sites distributed across the tropical dry forests of America. Tropical dry forests are depicted in dark grey (Portillo and Sanchez-Azofeifa, In press).

FIGURE 4-2. Scatterplots and Pearson correlation coefficients (*R*) between the proportion of forest lost and the number of fires (per 3 x 3km sample unit) for the study sites. Percentage of Dry Forest at Initial state of the time series (per each sample unit): A) >50% B) >60% C) >70% D) >80% E) >90%.

FIGURE 4-3. Forest / Non-Forest maps depicting deforestation events detected by change detection (red), remaining dry forest (dark green) and MODIS Active fires collected during 2002-2004 (Black points).

FIGURE 4-4. Scatterplots and Pearson correlation coefficients (*R*) between A) the number of dry forest fragments and the number of fires (per 3 x 3km sample unit) at each site and B) the number of dry forest fragments and percentage of area deforested (per 3 x 3km sample unit) at each site. (* $P < 0.001$, ** $P < 0.05$, others are not significant).

FIGURE 4-5. A) Scatterplot of the relationship between the Pearson correlation coefficient (*R*) computed and the percentage of area occupied by dry forest at the initial state of the time series (X axis). B) Scatterplot of the relationship between the number of sample units (n) and the percentage of area occupied by dry forest at the initial state of the time series. C) Range of Pearson correlation values for each interval of percentage of dry forest. The grey areas in A and B indicate that the region between 50-60% of area occupied by dry forests at initial state of time-series is where *R* stabilizes for all study sites and the number of sample units (*n)* is significant.

(Table 4-1)

		Initial state		Final state	
Site	**Land use**	**Satellite Imagery / Spatial resolution**	**Date of acquisition**	**Satellite Imagery**	**Date of acquisition**
Chamela, MEX	Slash-and-burn mixed crop agriculture and Cattle raising, tourism development	Advanced Spaceborne Thermal-Emission and Reflection Radiometer (ASTER) / 15-m	June 23rd (JD: 174), 2002	Advanced Spaceborne Thermal-Emission and Reflection Radiometer (ASTER) / 15-m	June 23rd (JD: 174), 2005
Machango, VEN	Subsistence agriculture and cattle raising	Landsat Thematic Mapper (TM)	July 2nd (JD: 183), 2001	Landsat Enhanced Thematic Mapper (ETM+)	July 29th (JD: 210), 2005
Santa Cruz, BOL	Intensive industrialized commercial agriculture, especially soybean production	Advanced Spaceborne Thermal-Emission and Reflection Radiometer (ASTER) / 15-m	May 23rd (JD:143), 2001.	Advanced Spaceborne Thermal-Emission and Reflection Radiometer (ASTER) / 15-m	May 22nd, JD:142, 2005.
Mata Seca, BRA	Commercial and subsistence mixed crop agriculture, coal production, cattle raising	Landsat Thematic Mapper (TM)	July 15th (JD: 196), 2001	Landsat Thematic Mapper (TM)	July 2nd (JD: 183), 2005

(Table 4-2)

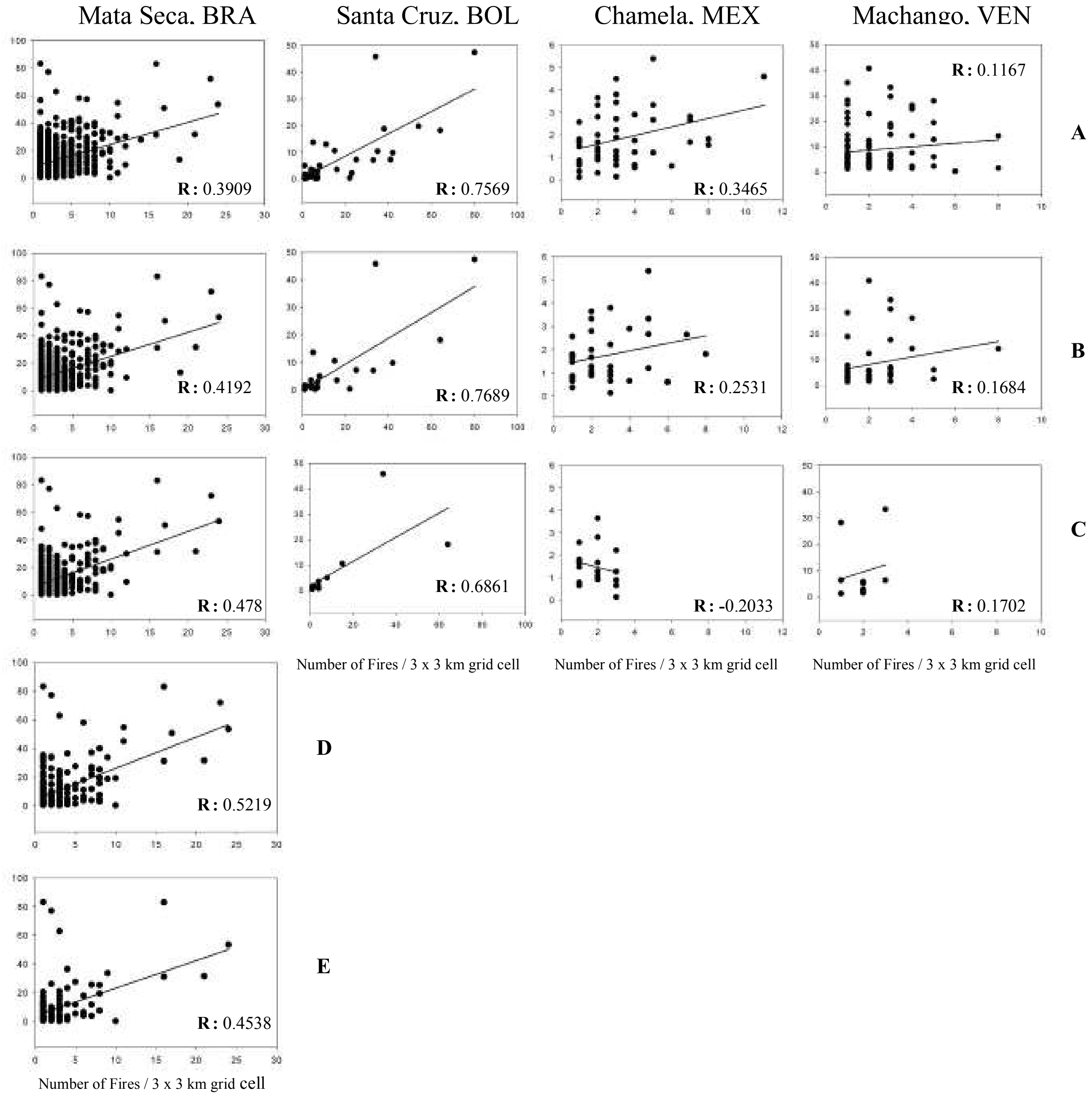
Data Collection	**Number of fires**	**Fire density (fires/km2)**	**Moran's I index**	***p*-value**	**Pattern of aggregation**	**Z-score**
Mata Seca,BRA						
2002-2004	3645	0.15	-1.48	1	Random	-1.48
Santa Cruz, BOL						
2002-2004	1740	0.47	0.03	0.01	Clustered	136.95
Chamela, MEX						
2002-2004	924	0.45	0.11	1	Random	0.09
Machango,VEN						
2002-2004	848	0.08	0.35	1	Random	0.86

(Table 4-3)

	Mata Seca			**Santa Cruz**			**Chamela**			**Machango**		
% Forest	***R***	LS	***n***	***R***	LS	***n***	***R***	LS	***n***	***R***	LS	***n***
>50	0.39	99.9%	735	0.76	99.9%	40	0.35	98.53	49	0.12	75.23	100
>55	0.40	99.9%	636	0.74	99.9%	35	0.37	98.72	45	0.17	83.66	70
>60	0.42	99.9%	540	0.77	99.9%	26	0.25	85.76	35	0.22	84.89	43
>65	0.45	99.9%	442	0.79	99.9%	16	-0.19	65.86	26	-0.06	22.98	23
>70	0.48	99.9%	359	0.69	98.6%	12	-0.20	59.61	19	0.17	36.18	10
>75	0.50	99.9%	286	0.43	43.2%	4	-0.61	80.22	6			
>80	0.52	99.9%	228									
>85	0.45	99.9%	169									
>90	0.45	99.9%	114									
>95	0.54	99.9%	64									

(Figure 4-1)

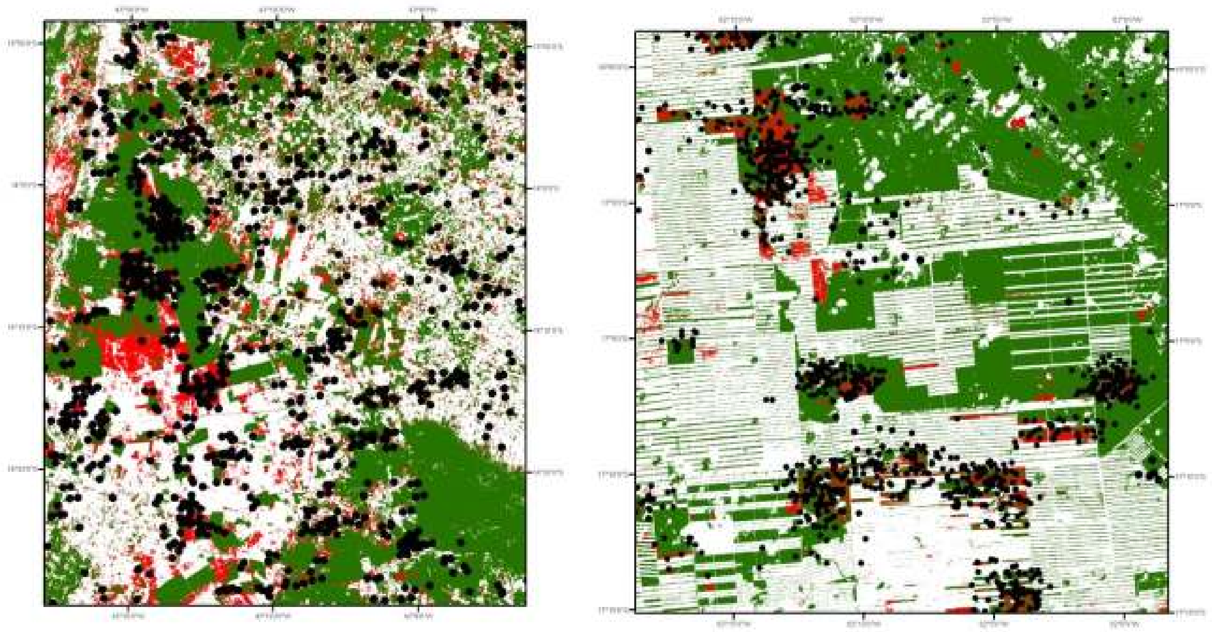
(Figure 4-2)


Mata Seca. BRA
Santa Cruz. BOL
Chamela. MEX
Machango. VEN
A
R: 0.3909
R: 0.7569
R: 0.3465
R: 0.1167
B
R: 0.4192
R: 0.7689
R: 0.2531
R: 0.1684
C
R: 0.478
R: 0.6861
R: -0.2033
R: 0.1702
D
R: 0.5219
E
R: 0.4538
Number of Fires / 3 x 3 km grid cell
Number of Fires / 3 x 3 km grid cell
Number of Fires / 3 x 3 km grid cell
Number of Fires / 3 x 3 km grid cell

(Figure 4-3)

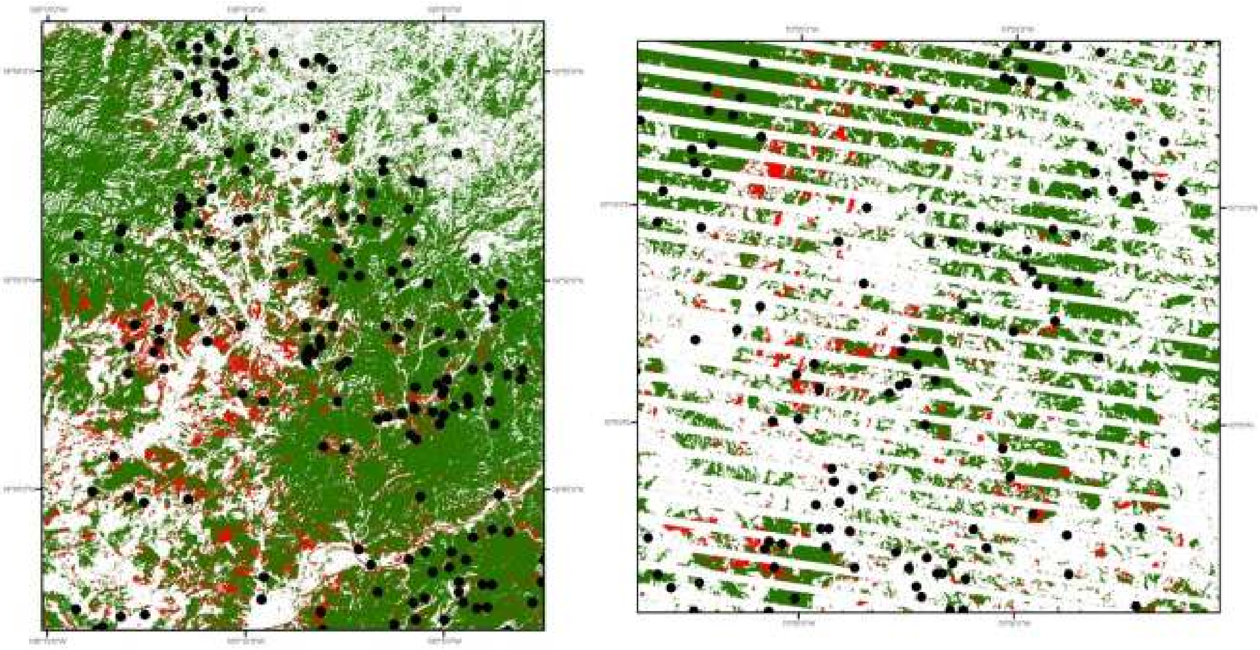
Mata Seca. BRA

Santa Cruz. BOL

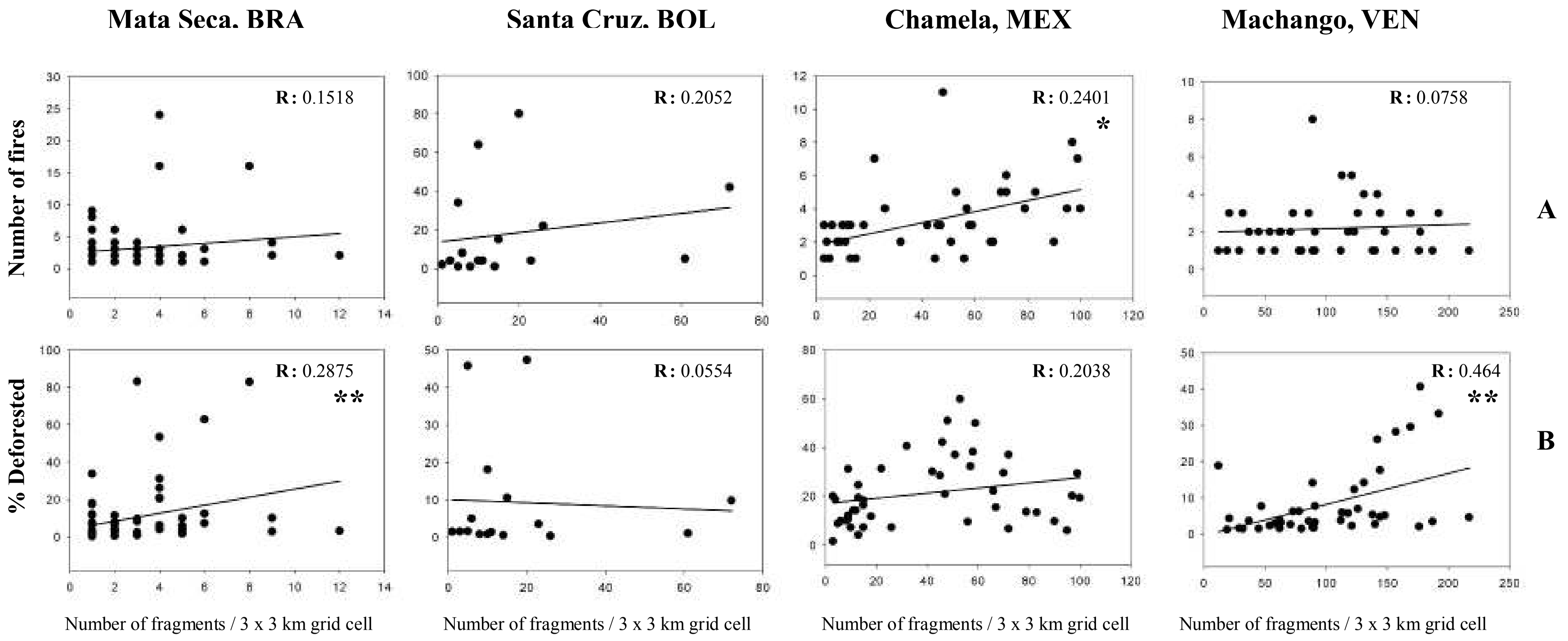


Chamela. MEX

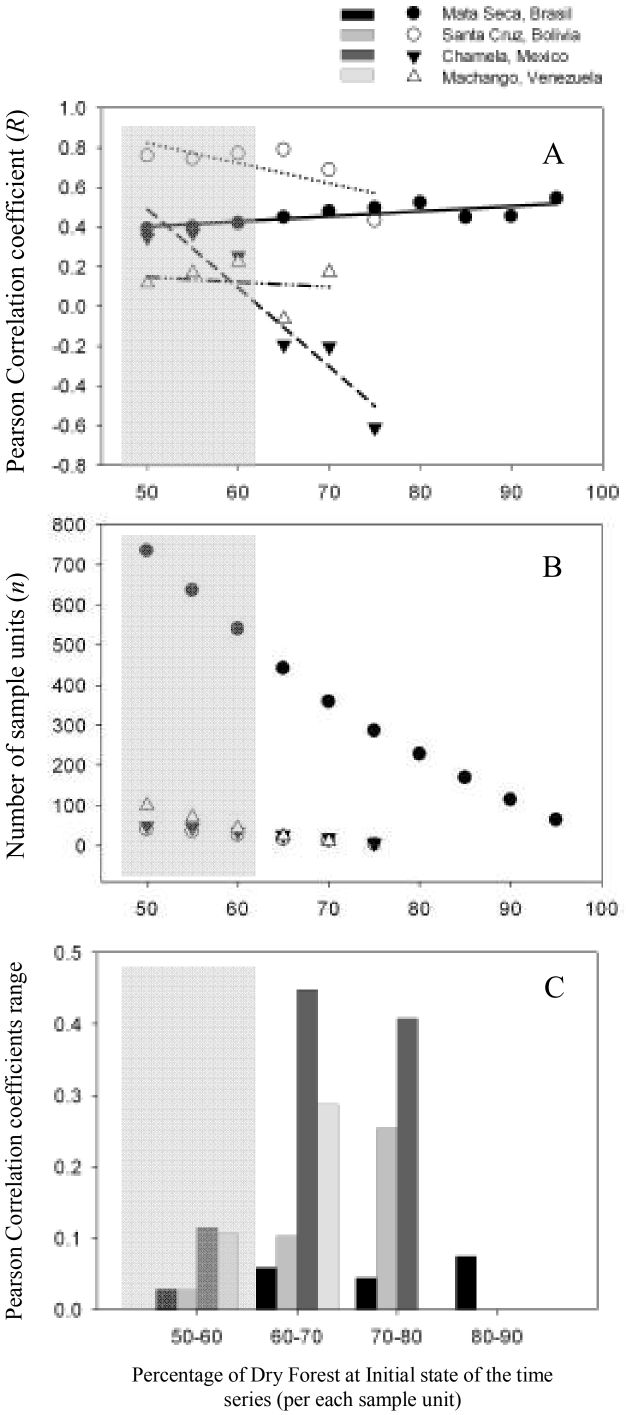
Machango, VEN



(Figure 4-4)


Mata Seca. BRA
Santa Cruz. BOL
Chamela, MEX
Machango, VEN
Number of fires
% Deforested
R: 0.1518
R: 0.2052
R: 0.2401
*
R: 0.0758
R: 0.2875
**
R: 0.0554
R: 0.2038
R: 0.464
**
A
B
Number of fragments / 3 x 3 km grid cell
Number of fragments / 3 x 3 km grid cell
Number of fragments / 3 x 3 km grid cell
Number of fragments / 3 x 3 km grid cell

(Figure 4-5)


Mata Seca, Brasil
Santa Cruz, Bolivia
Chamela, Mexico
Machango, Venezuela
A
Pearson Correlation coefficient (R)
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
50
60
70
80
90
100
B
Number of sample units (n)
800
700
600
500
400
300
200
100
0
50
60
70
80
90
100
C
Pearson Correlation coefficients range
0.5
0.4
0.3
0.2
0.1
0.0
50-60
60-70
70-80
80-90
Percentage of Dry Forest at Initial state of the time series (per each sample unit)

LITERATURE CITED

Achard, F., H. D. Eva, H.-J. Stibig, P. Mayaux, J. Gallergo, T. Richards, and J.-P. Malingreau. 2002. Determination of deforestation rates of the world's humid tropical forests. Science 297 (5583): 999-1002

Alves, R. 2008. Zonamento ambiental e os desafios da implementação do Parque Estadual Mata Seca, Municipio de Manga, Norte de Minas Gerais. Instituto de geociencias da Universidade Federal de Minas Gerais. Belo Horizonte, Brasil.

Castillo, A., A. Magana, A. Pujadas, L. Martınez, C. Godınez. 2005. Understanding the interaction of rural people with ecosystems: a case study in a tropical dry forest of Mexico. Ecosystems 8, 630–643.

Di Bella, CM.; EG Jobbaggy, JM Paruelo, Pinnock, S. 2006. Continental fire density patterns in South America. Global Ecology and Biogeography 15:192-199.

Dinerstein E., D. Olson, D. Graham, A. Webster, S. Primm, M. Bookbinder, G. Ledec. 1995. Una evaluación del estado de las Eco-regiones terrestres de América Latina y el Caribe . Banco Mundial, WWF. Washington D.C. 133 p.

Ellingson L.J.; Kauffman, JB, Cummings D.L., Sanford, R.L., Jaramillo, V.J. 2000. Soil N dynamics associated with deforestation, biomass burning and pasture conversion in a Mexican tropical dry forest. Forest Ecology and Management 137: 41-51.

Ewel, J.J. 1999. Natural systems as models for the design of sustainable systems of land use. Agroforestry Systems 45: 1–21, 1999.

Eva, H and Fritz, S. 2003. Examining the potencial of using remotely sensed fire data to predict areas of rapid forest change in South America. Applied Geography 23: 189-204

Eva, H. D., & Lambin, E. F. 2000. Fires and land-cover change in the tropics: a remote sensing analysis at the landscape scale. Journal of Biogeography, 27, 765–776.

Ehrlich, D., Lambin, E. F., & Malingreau, J.-P. 1997. Biomass burning and broad scale land-cover changes in Western Africa. Remote Sensing of the Environment, 61, 201–209.

ESRI (2008) ArcGIS 9.3 Desktop Software. Environmental Systems Research Institute. Redlands, CA. USA. http://www.esri.com

Fajardo, L., V. González, J. Nassar, P. Lacabana, C. Portillo Q., F. Carrasquel, & J.P. Rodríguez. 2005. Tropical Dry Forests of Venezuela: Characterization and Current Conservation Status. Biotropica 37 (4), 531-546.

FAO . 2005. Global Forest resources Assessment 2005: progress towards sustainable forest management. Food and Agriculture Organization of the United Nations, Rome 2006.

Fudeco. 2004. Dossier para el estado Lara. Fundación para el Desarrollo de la Región Centro Occidental de Venezuela. Barquisimeto, Venezuela. Available online at : http://www.fudeco.org

Geist, H and Lambin E. 2002. Proximate causes and underlying driving foreces of Tropical Deforestation. Bioscience 52 (2): 143-150

Giglio, L., J. Descloitres, C. O. Justice, and Y. J. Kaufman. 2003. An enhanced contextual fire detection algorithm for MODIS. Remote Sensing of Environment 87:273–282.

Giglio L. 2007. MODIS Collection 4 Active Fire Product User's Guide version 2.3. Science Systems and Application Inc. Available online at: http://maps.geog.umd.edu/firms/resources.htm

Hoekstra, J., T. Boucher, T. Ricketts, and C. Roberts. 2005. Confronting a biome crisis: global disparities of habitat loss and protection. Ecology Letters 8: 23–29.

Jensen, J. 2007. Remote Sensing of Environment: an earth resource perspective. 2nd Edition. Prentice Hall Series in Geographic Information Science. Pearson Prentice Hall, USA.

Kalacska M., G.A. Sanchez-Azofeifa, B. Rivard, T. Caelli, H. Peter White, and J.C. Calvo-Alvarado. 2007. Ecological fingerprinting of ecosystem succession: Estimating secondary tropical dry forest structure and diversity using imaging spectroscopy. 108 (1): 82-96.

Kennard D.K; Gholz, HL. 2001. Effects of high and low intensity fires on soil properties and plant growth in a Bolivian dry forest. Plant and Soil 234:119-129.

Killeen, T. J., V. Calderon, L. Soria, B. Quezada, M. K. Steininger, G. Harper, L. A. Solórzano; C. J. Tucker. 2007. Thirty years of land-cover change in Bolivia. *Ambio* **36**: 600–606.

Leica Geosystems (2008) ERDAS Imagine 9.2. Leica Geosystems Geospatial Imaging. Norcross, GA . USA.

Mas, J.-F. 1999. Monitoring land-cover changes: a comparison of change detection techniques. Int. J. Remote Sensing 20 (1):139-152.

Mayaux, P.; Holmgren, P.; Achard, F.; Eva, h. Stibig, H-J; Branthomme, A. 2005. Tropical forest cover change in the 1990’s and options for future monitoring. Phil.Trans.R. Soc. B. 360:373-384.

Mehta, V.K; Sullivan P; Todd W.M; Krishnawamy J; DeGloria, S. 2008. Ecosystem Impacts of disturbance in a dry tropical forest in Southern India. EcoHydrology 1, 149-160.

Miles, L., A. Newton, R. DeFries, C. Ravilious., I. May, S. Blyth, V. Kapos. and J. Gordon. 2006. A global overview of the conservation status of tropical dry forests. Journal of Biogeography. 33, 491-505

Millenium Ecosystem Assessment. 2005. Chapter 5: Ecosystems Condition and Human Well-being. In: Ecosystems and Human Well-being: Current State & trends Assessment. Millenium Ecosystem Assesment Board. Island press.

Morton, DC; DeFries, R.; Randerson, J.T.; Giglio, L.; Schroeder, W.; Van der Werf, G.R. 2008. Agricultural intensification increases deforestation fire activity in Amazonia. Global Change Biology 14:2262-2275.

Olson, D. M, E. Dinerstein, E.D. Wikramanayake, N.D. Burgess, G.V.N. Powell, E.C. Underwood, J.A. D'amico, I. Itoua, H.E. Strand, J.C. Morrison, C.J. Loucks, T.F. Allnutt, T.H. Ricketts, Y. Kura, J.F. Lamoreux, W.W.Wettengel, P. Hedao, & K.R. Kassem. 2001. Terrestrial Ecoregions of the World: A New Map of Life on Earth. BioScience 51:933-938.

Portillo C. & Sanchez A. (2010) Extent and Conservation of tropical dry forests in the Americas. Biological Conservation 143:144-155.

Ruiz J.; fandino MC; Chazdon RL. 2005. Vegetation structure, composition and species richness across a 56-year chronosequence of tropical dry forest on Providencia Island, Colombia. Biotropica 37 (4):520-530

Sánchez-Azofeifa, G. A.; M. Quesada; J. P. Rodríguez; J. M. Nassar; K. E. Stoner; A. Castillo; T. Garvin; E. L. Zent; J. C. Calvo-Alvarado; M. Kalacska; L. Fajardo; J. A. Gamon & P. Cuevas-Reyes. 2005. Research Priorities for Neotropical Dry Forests. Biotropica 37 (4), 477-485.

Sanchez-Azofeifa, G.A., Quesada, M., Cuevas-Reyes, P., Castillo, A., Sanchez-Montoya, G. In press. Land cover and conservation in the area of influence of the Chamela-Cuixmala Biosphere Reserve, Mexico. Forest Ecol. Manage. 258:907-912

Steininger MK, Tucker CJ, Ersts P, Killeen TJ, Villegas Z, Hecht SB (2001) Clearance and fragmentation of tropical deciduous forest in the Tierras Bajas, Santa Cruz, Bolivia. Conserv Biol 15:856–866

Steininger MK, Tucker CJ, Townshend JRG, Killeen TJ, Desch A, Bell V, Ersts P. 2001b. Tropical deforestation in the Bolivian Amazon. Environ Conserv 28:127–134.

Stoner, K. 2005. Phyllostomid Bat Community structure and Abundance in two contrasting tropical dry forests. Biotropica 37(4):591-599.

Turner, B. L., Skole, D., Sanderson, S., Fischer, G., Fresco, L. & Leemans, R. 1995. Land-use and land-cover change; science/ research plan. IGPB report no. 35, 132. International Geosphere–Biosphere Programme, Stockholm.

Wright, S.J., Sanchez-Azofeifa, G.A., Portillo-Quintero, C., Davies, D. 2007. Poverty and corruption compromise tropical forest reserves. Ecological Applications, 17(5), 2007,1259-1266.

CHAPTER 5- Edge Influence on canopy openness and understory microclimate in two neotropical dry forest fragments

INTRODUCTION

One of the most widespread anthropogenic changes to ecosystem integrity is the fragmentation and degradation of continuous vegetation through deforestation (Aizen & Feisinger, 1994). . Deforestation affects biological diversity through direct destruction of habitats and through habitat fragmentation (Skole & Tucker, 1993). In addition, one of the major changes brought about by habitat fragmentation to tropical forests is an increase in the proportion of edge exposed to other habitats (Kapos et al. 1997, Laurance & Curran, 2008). Abrupt exposure to different environmental conditions indirectly alters microclimate therefore increasing tree mortality rates and decreasing plant species recruitment (Asquith & Mejia-Chang, 2005, Laurance et al.1998.). Direct changes include changes in air temperature, soil moisture, relative humidity and the amount of light penetrating the forest understory (Kapos et al. 1997; Pohlman et al. 2006).

Another effect of fragmentation is the exposure of the perimeter to windthrow. Winds striking an abrupt forest edge can exert strong lateral-shear forces on exposed trees and create considerable downwind turbulence for at least 2-10 times the height of forest edge (Laurance & Curran, 2008). These conditions make treefall gaps more frequent near the edges of a forest fragment (Kapos et al. 1997, Laurance & Curran, 2008). In general, tree damage leads to reduced canopy cover and greater abundance of snags and logs at edges (Harper et al. 2005). Typical vegetation responses to these changes in edge environment result in an increased presence of exotic and disturbance-adapted species, increased sapling and tree densities, increased shrub cover, and higher species richness (Gelhausen et al. 2000; Harper et al. 2005, Laurance et al. 2002). Animal communities are also affected by these changes. Near edges, there is an increase in disturbance-adapted butterflies and beetle species, an alteration of the species composition of leaf-litter invertebrates, changes in behavioral and biological characteristics in small mammal populations, and changes in the number and structure of bird communities (Laurance et al. 2002; Manu et al. 2007; Fuentes-Montemayor, 2009; Laurance, 2004). Ecological processes such as seed dispersal and predation, nest predation, brood parasitism, and herbivory are also affected by distance from the edge of the forest fragment (Murcia 1995). For most of abiotic and biotic edge effects in tropical rainforests, Laurance et al. (2002) and Harper et al. (2005) estimate that some ecological processes can be affected up to 300-400 m from the forest edge. These authors also report that edge effects have shown higher magnitude and penetration distance in recently created edges (<7 years old) and tend to be reduced and become stabilized with time in older maintained tropical rainforest edges (≥ 7-12 years).

Edge influence on forest structure and composition has been studied in tropical rainforest, temperate and boreal ecosystems. In the tropics, long-term systematic research on edge effects has been conducted mostly in fragmented rainforests, especially within the framework of the Biological Dynamics of Forest Fragments Project (BDFFP) in the Brazilian Amazon, a project launched in 1979 by the World Wildlife Fund and the

Brazil's National Institute for Research in Amazonia (INPA) (Bierregard et al. 1992). Other biodiversity-rich ecosystems subjected to different ecological dynamics such as tropical dry forests haven't been assessed in these terms. Tropical dry forests (TDF) have been transformed and occupied by urban and agricultural areas at significantly higher rates than tropical rainforests (Murphy & Lugo, 1986) and most of their extent remains within lowland human dominated landscapes (Portillo & Sanchez-Azofeifa, 2010), however, the magnitude and penetration distance of edge effects in tropical dry forests (TDF) remains poorly studied and unknown in much cases.

Harper et al. (2005) suggest that forests that are subject to frequent natural disturbances may exhibit lower magnitude or distance of edge influence. Here, edge creation may have relatively little impact on the forest composition and structure. Such resilience is characteristic of the TDF ecosystem, which is characterized by ecological processes adapted to seasonal fluctuations of water availability. The TDF ecosystem has been historically subjected to pressures from human disturbance and is considered capable of recovering more quickly after disturbance (Segura et al. 2003, Murphy & Lugo, 1986). However, Quesada et al. (2009) point out that, in fact, evidence suggests that TDF are more susceptible to human disturbance because growth rate and regeneration is slow, reproduction is highly seasonal, and most plants are mainly outcrossed and dependent on animal pollination. Quesada et al. (2009) also point out the importance of light dynamics (gap dynamics) in the regeneration of TDF after disturbance, and suggest more efforts to understand ecological processes of this ecosystem.

In this paper, we present results from eight edge-to-interior transects surveyed in two TDFs fragments (old maintained edges) located in Venezuela and Brazil. The specific objective of this study is to evaluate the magnitude and distance of edge influence on the amount of visible light penetrating the canopy and the magnitude and distance of edge influence on understory microclimate conditions. Based on previous syntheses on the mechanisms and processes that follow edge creation in tropical forests (Laurance et al. 2002; Harper et al. 2005), and the assumptions on the resilience capacity of TDF to disturbance (Segura et al. 2003, Murphy & Lugo, 1986), we predict that edge creation has little impact on TDF environmental conditions. Such resilience should be more evident in older maintained edges, were rapid secondary vegetation growth would have facilitated the sealing process at the edge (edge-closure). Although the current study does not extend to changes in biotic properties (e.g. species composition, tree mortality), we believe that studying abiotic edge-to-interior gradients in TDF is an important step to understand the degree of disturbance following fragmentation in TDFs.

METHODS

Study sites

We selected two TDFs fragments to conduct the edge effect surveys. One is located within the Parque Estadual da Mata Seca in Brazil, and the second within the Hato Piñero Private Wildlife Refuge in northern Venezuela (See Figure 5-1). Both fragments represent remnants of mature TDFs within agricultural and cattle ranching land use matrices (Alves, 2008; Bertsch & Barreto, 2008). Measurements at each site were made during the wet season (Between May and June 2007 for Hato Piñero and between December 2007 and January 2008 for the Mata Seca site), when there were fully expanded canopy leaves.

Parque Estadual da Mata Seca, Minas Gerais, Brazil (MS site)

The Parque Estadual da Mata Seca is a provincial conservation unit located along the border of northern Minas Gerais state and south-western Bahia state in Brazil and is centered at 14°50'50"S and 43°58'43."W. The region is mainly surrounded by agricultural lands and highly fragmented remnants of dry forest within the Atlantic Dry Forest and the Caatinga ecoregion of eastern Brazil. The Parque Estadual da Mata Seca was created in the year 2000 in order to preserve important remnants of diverse vegetation formations such as tropical deciduous forests, riparian forests and “Furados” or open arboreal caatinga. Tropical Dry forests are found where eutrophic soils of calcareous origin favor the development of a tall deciduous vegetation, which can reach up to 20-30 m high (Alves, 2008). The site has a mean annual temperature of 24ºC and an annual rainfall is 916 mm. Rainfall is highly seasonal with a dry season that extends for almost 7 months from May until November. Most of the rainfall concentrates between November and April (Alves, 2008). The forest fragment studied is located at the center of the site and is surrounded by a secondary TDFs, open pastures and agricultural land.

Hato Piñero, Cojedes State, Venezuela (HP site)

The Hato Piñero is a private cattle ranch situated in the Central Venezuelan Llanos in Cojedes State (8°52'45.79"N, 68° 9'10.58"W). The site is a mosaic of pastures, savannas, dry forests and gallery forests. Average annual temperature and precipitation is 27.5°C and 1,469.6 mm, respectively. The area presents a strong seasonality with a rainy season occurring from April to November and a dry season from December to March (Bertsch & Barreto, 2008). The forest fragment studied is located in the center of the ranch occupying approximately 30,000 ha. These forests are medium tall (25-30 m), semi-deciduous or deciduous, with almost its southern half subjected to flooding in the rainy season. The site has been established as a private conservation unit since 1953 with limited selective logging, no wildlife hunting, fire control and protection of dry forest remnants. In 2005, the Venezuelan National Land Institute, under a land reform campaign that aims to break up large landholdings to distribute among farmers, announced the confiscation of Hato Piñero and all its assets (http://www.branger.com). It is expected that this action will threaten current sustainable wildlife protection regimes and land use patterns in the Hato Pinero conservation area.

Sampling design

We conducted a sampling scheme adapted from Runkle (1992), Kapos, V. (1997), Laurance, W. (1997), Gerwing J. (2002), Kalacska et al. (2005), Souza, C. (2005) and

Pohlman et al. (2007). We established 500 m transects from the edge of the fragment into the forest interior in four locations at each site. Each transect allowed to perform surveys at several intercepts of the following variables: total canopy gap fraction, fraction of intercepted photosynthetically active radiation (FiPAR), Canopy Openness, Leaf Area Index and microclimatic variables such as temperature, relative humidity and photosynthetically active radiation at the forest understory. Two contiguous parallel transects were established at each location in order to include more sampling effort for each transect intercept. Total forest area surveyed at each location covered 0,03 km^2. For each site, two transects were located in edges exposed to linear openings (unpaved roads approximately 10 m wide), and two transects were located in edges facing open pastures (large forest clearings with little to no forest vegetation regrowth) in order to include exposure to different conditions at the matrix. Because of limited amount of comparable edges on mature TDF, transect selection did not took into account effects of edge aspect and exposure to prevailing wind and solar radiation conditions. Figure 5-2 shows the sampling design for each transect. An explanation of the variables measured follows.

Gap fraction

A gap refers to an area within the forest where the canopy (leaf height of tallest stems) is noticeably lower than in adjacent areas (Runkle, 1992). Gaps in the forest are generally created by the death of one or more canopy trees. In forest edges, increased tree mortality and damage as a consequence of wind throw result in more frequent tree-fall gaps (Laurance et al. 2002). To measure gap size*,* 60-m (width) x 50-m (length) plots were surveyed along the transects from the edge to 500 m inside of forest (for a total of 10 plots, see Figure 5-2). The dimensions (width and length) of all forest canopy gaps - areas with no canopy above 3-5 m (following Kapos et al. 1997) - were measured within each plot. Gap size was calculated following the Runkle (1992) formula which assumes elliptical dimensions for every tree-fall gap and transformed to represent the percentage of the total plot area using the following formula:

$$\text{Gap Fraction} = \{ [(\pi * \text{gap length} * \text{gap width}) / 4] / \text{plot area} \}. \qquad (1)$$

Fraction of Intercepted Photosynthetically Active Radiation (FiPAR)

The fraction of intercepted PAR has been used to capture forest canopy light absorption dynamics and canopy structure (Gamon et al. 2005; Serbin et al. 2009; Olofsson et al. 2007). FiPAR is measured by contrasting below canopy downwelling PAR readings to above canopy downwelling PAR readings. FIPAR is calculated using the formula:

$$\text{FiPAR} = (\text{Id A} - \text{Id B}) / \text{Id A} \qquad (2)$$

where Id A represents downwelling PAR radiation above the canopy, and Id B represents downwelling PAR radiation below the canopy. In order to measure FiPAR, transects were surveyed at 13 line intercepts located at 0, 10, 25, 50, 100, 150, 200, 250, 300, 350, 400, 450, and 500 m from the edge of the forest. At each line intercept, we used a Li-190

Line Quantum Sensor (LI-COR Biosciences) to measure Id B at the intercept, and at 7.5 m from the intercept (left and right). Data collection was made at breast height. Id A was monitored on a large clearing outside the forest using a PAR sensor (S-LIA-M003, Onset Computer Corp.) connected to a Hobo data logging weather station (Onset Computer Corp.). The Line quantum Sensor averages photosynthetic photon flux density (PPFD) over its one meter length (LI-COR Inc. 2010); which excluded the possibility of spatial autocorrelation between measurements.

Canopy Openness and Plant Area Index (PAI)

We estimated canopy openness in 13 transect intercepts located at 0, 10, 25, 50, 100, 150, 200, 250, 300, 350, 400, 450, and 500 m from the edge of the forest in each transect. At each line intercept, we took hemispherical photographs of the forest canopy (using a Nikon CoolPix 995 camera) at 7.5 m from the intercept (Left and right). Photos were taken at 1.5 m camera height. According to Chong et al. (2008), hemispherical photographs taken at approximately 1.5 m from the ground records wood and foliage for as much as 11 m around the sampling location for mature TDFs. Therefore, the distance maintained between measurements also discards the possibility of spatial autocorrelation between measurements. The photographs were processed with the Canopy Gap Light Analyzer v. 2.0 (SFU-IES 1999) in order to extract canopy structure information from the hemispherical photographs. From each hemispherical photograph, we quantified the percentage of canopy openness (percentage of open sky seen from beneath the forest canopy) and plant area index – PAI 4 Ring- (Kalacska et al. 2005), which is the effective leaf and woody area index integrated over the zenith angles 0 to 60°.

Understory Microclimate

At forest edges, elevated light penetration and wind throw affect environmental conditions at the understory (Kapos et al. 1997; Pohlman et al. 2006, Laurance et al. 2002). Changes in relative humidity, air and soil temperature at the understory can affect sapling and tree densities, favoring disturbance-adapted plant species and changing species richness and composition (Gelhausen et al. 2000; Laurance et al 2002). We investigated microclimatic edge gradients by measuring temperature, relative humidity and PAR in 9 transect intercepts located at 0, 4, 8, 12, 16, 20, 30, 50 and 100 m. Measurements were taken at 4 heights from the ground: 30 cm, 1 m, 2 m and 3 m. This sampling scheme was applied following Pohlman et al. 2006. A HOBO PAR Smart Sensor (Onset Computer Corporation) and a Hobo Temperature/Relative Humidity Smart sensor (Onset Computer Corporation) were mounted on an extendible pole and connected to a Hobo data logging weather station. I allowed the monitoring system to record microclimatic measurements during two minutes at each height. At each measurement, the PAR sensor was leveled to a horizontal fixed position. Data collection was undertaken, as quickly as possible, in clear or relatively clear (cloudy or overcast but not rainy) weather between 0800 h and 1000 hr when the light environment at the understory is relatively stable (Chazdon et al. 1984).

Analyses

We examined differences in gap fraction, FiPAR, canopy openness, LAI and microclimate as a function of distance from the edge using parametric one-way ANOVAs, and non-parametric Kruskal-Wallis one-way ANOVAs. Most canopy structural changes due to tree damage and mortality (Gap fraction, FiPAR, Canopy Openness and LAI) occur within the first 100 from the edge and forest interior conditions are reached after 300-400 m from the edge (Laurance et al. 2002, Harper et al. 2005). Following Turton et al. (1997), we grouped values in categories of “distance from edge” for the statistical analyses. Comparison was made at three different categories: 0-100, 150-300, 350-500 m. Regarding microclimatic variables, previous studies have shown that most edge-related changes occur within 40 m from the edge (Pohlman et al. 2007, Laurance et al. 2002, Harper et al. 2005), and that conditions at 100 m are similar to the undisturbed forest interior (Pohlman et al. 2007, Turton et al. 1997). For assessing microclimatic differences as a function of distance from edge, statistical differences were examined between three different categories: 0-10, 10-30, 50-100 m.

RESULTS AND DISCUSSION

Overall, results show a persistent physical and structural response of TDFs fragments to edge exposure even >25 years after fragmentation. All variables were affected significantly with distance from forest edge in at least one of the treatments and sites sampled. A description of results for each variable follows.

Gap fraction

Gap fraction was noticeably affected by distance to edge in all dry forest transects studied. Abrupt changes in canopy height due to tree-fall gaps were more frequent in the first 300 m from edge. Generally, gaps reached dimensions of 10 -15 m in width/length created by the collapse of one single tree. Other gaps were formed by the collapse of two or more trees creating a larger gap. These larger gaps were approximately 30-40 m in width/length. Figure 5-3 shows that the percentage of area in forest gaps increases with distance and reaches a peak at 150-300 m from edge (mid-distance) in most treatments. This pattern has been previously identified for tropical rainforests (Laurance et al. 2002) associated to the edge-closure phase where the edge is partially sealed by vegetation re-growth at the edge but treefall gaps proliferate partly as a result of increased windthrow. In Mata Seca (MS), gap fraction values in both treatments (open pastures (OP) and linear openings (LO)) varied significantly with distance from the forest edge ($F_{2,7}$= 6.57_{OP} ; $F_{2,7}$= 21.13_{LO}, all $P < 0.05$) showing a similar pattern of mid-distance increase in canopy gap area. In Hato Piñero (HP), gap fraction values in edges exposed to open pastures were not affected significantly with distance from edge (all $P > 0.05$). Here, gaps did not showed an increase at mid-distances and values varied similarly along the 500-m transects. Gap fraction values in edges exposed to linear openings at the HP site, did not show any statistically significant difference with distance from forest edge. However, an increase in accumulated gap fraction at mid-distances was evident (See Figure 5-3).

Fraction of Intercepted PAR

In contrast to gap fraction where actual forest structural and physical changes at the canopy level were measured, FiPAR measurements reflect the amount of photosynthetically active light intercepted by the canopy and sub-canopy leaves. FiPAR is thus an indicator of forest canopy and sub-canopy openness which is affected, not only by the frequency and size of treefall gaps but also by exposition to lateral light penetration at the edge. At the open pasture treatment in the MS site, FiPAR values varied significantly with distance from forest edge (H= 34.37, $P < 0.01$) increasing toward the forest interior. At the MS site, in linear openings, FiPAR did not differ significantly with distance since light penetration remained low as far as 300 m into the forest interior. The effect of distance in this treatment, however, was close to statistical significance (H= 4.9, P = 0.08) supporting the strong trend of FiPAR values increasing as it approaches forest interior conditions (see Figure 5-3). At the HP site, FiPAR values in both treatments were affected with distance from edge (all $P < 0.05$). FiPAR showed sensitivity to both lateral light penetration from edge exposure and changes in downwelling PAR reaching the forest understory as a result of canopy gaps. This is evidenced in Figure 5-3, where abrupt decreases occur in FiPAR values at the forest edge (0-10 m) and at mid-distances in all treatments. The decline of values at mid-distances was closely related to the occurrence of large canopy gaps as registered by gap fraction measurements.

Canopy Openness and Plant Area Index (PAI)

Differences in canopy openness (measured from hemispherical photographs of the forest canopy) as a result of edge influence showed dissimilar responses between treatments. In open edges at the MS and HP site, the range in the percentage of canopy openness was very similar throughout the 500-m transect with only an abrupt increase in the first 10-m as a result of exposure to lateral light penetration from the edge. In open edges, analysis showed no significant difference in canopy openness values with distance from the edge (all $P > 0.05$). In Linear openings at both sites, however, canopy openness varied significantly with distance from edge (all $P < 0.01$) showing an abrupt decrease in the first 10 m and slightly decreasing towards forest interior low openness conditions (canopy openness 10-15%). Similarly to canopy openness, PAI calculated from hemispherical photographs was responsive to increased lateral light exposure at the very edge of the forest (0-10 m) in all treatments and showed no significant difference with distance from edge in open edges. In Linear openings, PAI calculations reflected a slight continuous increase in values towards forest interior conditions (~2.5 PAI). In general, canopy openness and plant area index measurements from hemispherical photos were sensitive to lateral light penetration but showed no obvious response to canopy disturbance from treefall gaps at mid-distances from the edge. The lack of sensitivity at these mid-distances might be due to an observed increased density of understory vegetation. When hemispherical photographs are taken at approximately 1.5 m from the ground, final Canopy Openness and PAI estimates usually include the woody and foliage component from the understory for as much as 11 m around the sampling location

(Chong et al. 2008). Abundant foliage from the understory can mask a large proportion of a hemispherical photograph yielding low values of Canopy Openness in areas where the canopy might be actually open and affected by tree fall gaps. Although, this study did not include a survey of understory vegetation biomass, an increased abundance of understory vegetation at mid-distances from the edge was observed. In fact, one of the most generalized responses to edge creation and increased light penetration in tropical forests is an increased diversity and abundance of saplings, herbs and shrubs with a resultant increased in understory foliage density (Kapos et al. 1997; Laurance et al. 2002, Harper et al. 2005). Therefore, contrarily to FiPAR measurements, Canopy Openness and PAI values might have been affected by a higher abundance of understory biomass at mid-distances.

Understory microclimate

In the tropical dry forest sites studied, understory microclimate variables were affected significantly by distance from edge (Figure 5-4**,** Table 5-2).

Variability in temperature and PAR was higher in the MS site than in the HP site. Temperatures ranges were similar across treatments and sites (between 25 and 27°C) but light environment at the understory was different. PAR readings in the HP site were maintained relatively low and stable (<100 µmol/m^2/sec) throughout the 100 m transect, while in the MS site, values ranged from ~50 to >400 µmol/m^2/sec. Ranges in relative humidity between sites were also different. The HP site was more humid than the MS site at the understory. The HP site shows values >80% in relative humidity while the MS site showed values ranging from 60 to 80 % in relative humidity. At the 0-intercept, temperature, relative humidity and PAR values resembled those found at 100-m. Subsequently, temperature and PAR values decreases at 4-16 m from edge (and relative humidity increased correspondingly) and then swiftly increases towards 100-m conditions. This trend was stronger at the MS site than at the HP site where the pattern was more subtle (See Figure 5-4). In the HP site, microclimatic conditions were less variable and more stable throughout the transect, therefore resembling forest interior conditions.

In general, response to edge influence showed similar directionalities. Table 5-2 shows median values for categories of distances from the edge (0-10 m, 12-30 m, 50-100 m). The results show that for all transects in MS and HP, PAR increases, temperature increases and relative humidity decreases as a function of distance from forest edge. In Figure 5-5 (a 3D scatter plot using PAR, Relative humidity and Temperature) clearly demonstrates that the distribution of the values of the three variables changes towards the forest interior following the same direction.

Figures 5-4 and 5-5 also show that light conditions at the MS site were highly variable even at 100 m from the forest edge. Here, we found values of PAR at the 100-m intercept that did not resemble tropical forest interior conditions (Chaves & Avalos 2008, Chazdon et al. 1984). This can be the result of particular characteristics in dry forest structure and biological dynamics (Murphy & Lugo, 1986, Quesada et al. 2009), or the result of persisting disturbance from edge influence. Further research on understory microclimate at this site should evaluate the use of longer transects (~500 m) in order to corroborate if light conditions stabilize towards the interior of the forest fragment. . Also, studying the impact of rainfall seasonality and phenology on dry forest edge dynamics will improve our understanding on the resilience and restoration capacity of the dry forest ecosystem. At both sites, lower temperature and PAR values at the 4-16 m intercepts seem to correspond with an observed increase in density of understory and subcanopy foliage.

Overall analysis

Based on our observations and data collected, some generalities related to edge effects can be drawn across transects and sites.. In the first 10 m from the forest edge, lateral light penetration through the canopy and subcanopy layers is high. Generally, logs and branches from damaged and fallen trees in the forest floor were visibly more frequent in the first 0-25 m. Vegetation abundance at the forest subcanopy and understory layers was also noticeably higher here than in the forest interior (>400 m from edge). After 100 m, canopy gaps start to appear more often and larger in size, usually created by fallen tall trees (15-20 m height) that now lied on the forest floor, in some cases bringing down adjacent trees and/or their branches to the ground. The occurrence of larger treefall gaps at the 150-300 range was seen in all treatments and all sites resembling the edge response of humid forests as a result of increased windthrow (Laurance & Curran, 2008). In these gaps, lianas and tree saplings were present and generally reached a height of 3-5 m.. After the 300-m intercept, forest understory vegetation was more sparse and evenly distributed, while canopy and subcanopy layers were more continuous and less interrupted by tree-fall gaps, which at these distances were less frequent and smaller in size.

The edge effect profile observed was similar in all sites. Measured canopy gap fraction clearly showed such alterations of canopy and subcanopy structure as a result of edge influence. FiPAR measurements were able to capture these variations while canopy openness and PAI measurements from hemispherical photographs only captured changes occurring at the very edge of the forest. The effect of edge influence on temperature, PAR and relative humidity was stronger at the MS site and seem to penetrate further than 100-m. Data collected showed that the HP site was more humid and shaded than the MS site. At the HP site, values were relatively stable throughout the transect showing only subtle decreases in PAR and temperature between the 4-16 m intercept. A decrease in PAR and temperature at these distances was also registered for the MS site. Overall, microclimatic conditions were similarly affected by distance from edge in all sites. Temperature, as well as PAR, increases with distance from edge, with a correspondent decrease in relative humidity as temperature increases. A similar confounded response of these variables (PAR and temperature increases, relative humidity decreases) has already been reported in edges of tropical humid forests, especially related to a decreasing gradient of subcanopy vegetation density (Didham & Lawton 1999; Jose et al. 1996).

Our results indicate that the edges studied in this work situate in the post-closure phase. In this phase secondary responses often result in the development of a sidewall of dense vegetation that fill in open spaces at the edge (Laurance et al. 2002, Harper et al. 2005). Tree damage and canopy gap proliferation are still high due to persistent elevated windthrow. Results in gap fraction and FiPAR show that edge influence at these sites extends to at least 300-m into these dry forest fragments. The edges studied in these forest fragments are older edges (> 25 years since creation). According to Harper et al. (2005), edge effects in older humid forest edges should be considered attenuated and affecting less than 50-100 m into the forest. However, then dry forest edges studied here, showed similar responses to young or newly created humid forest edges. Both magnitude and distance of edge influence remains strong, despite the edge seems to be sealed by secondary growth. A plausible explanation is that biophysical and ecological characteristics of tropical dry forests play an important role in determining resilience to edge effects. A tropical dry forest have lower basal area and stature than a humid forest (Pennington et al. 2006) which can make it structurally more vulnerable to lateral light penetration, striking lateral winds and gap formation following edge creation. Severe drought conditions and seasonality might be also an important factor perpetuating the strong edge influence.

CONCLUSIONS

More than half of tropical dry forests have been transformed globally (Miles et al. 2006) in the Americas, and only 44% of their extent are left in the Americas (Portillo & Sanchez-Azofeifa, 2010). Most of its extent survives in lowland human dominated landscapes under less strict legal protection than rainforests and threatened by crop cultivation, cattle ranching and tourism expansion (Portillo & Sanchez, 2010). Deforestation for land development and road construction has converted areas that were once continuous and relatively uninterrupted dry forests to fragmented landscapes of small and large forest remnants embedded in agricultural and road matrices. One of the major changes brought about by habitat fragmentation to tropical forests is an increase in the proportion of edge exposed to other habitats (Kapos et al. 1997, Laurance & Curran, 2008). However, edge evolution through time (structural and biological dynamics during edge creation, closure and sealing processes) has been mostly studied in humid forests. In this work, we presented results from edge-to-interior surveys in two tropical dry forest fragments where we assessed the edge influence on important indicators of canopy structure, integrity and functionality (Gap fraction, FiPAR, Canopy Openness and PAI) and the edge influence on understory microclimate variables that are critical in determining ecological processes such as plant growth, decomposition and nutrient cycling (Sizer & Tanner, 1999; Turton et al. 1997; Laurance et al. 1998).

Measurements of canopy gap fractions across transects clearly indicate a physical and structural impact of edge exposure that extends up to 300 m from the forest edge into the forest interior on both tropical dry forest fragments studied. Treefall gaps proliferate between 150-300 m from the forest edge. FiPAR results showed that light penetration to the understory increases at the edge of the forest and around created treefall gaps. This increment in light availability in the understory might be favoring an observed (but not documented) increase in abundance of understory vegetation at the edge and around treefall gaps. Temperature and relative humidity were also affected by edge conditions. Although edges were created >25 years ago, penetration of primary processes (tree damage) following edge creation is still high in magnitude and distance. Tree biomass, seasonality, plant growth rate and reproduction dynamics might play an important role in determining restoration (Quesada et al., 2009) and edge evolution in TDFs fragments. We suggest that further research on the response of biological dynamics to edge creation (both in wet and dry seasons) is needed in order to better understand the resilience and regeneration capacity of TDFs to fragmentation.

TABLE LEGENDS

TABLE 5-1. One-way analyses of variance (F-ratio and Kruskal-Wallis tests) showing the effects of distance from the edge on gap fraction, FiPAR, canopy openness and PAI for each site and edge type.

TABLE 5-2. One-way analyses of variance (Kruskal-Wallis tests) showing the effects of distance from the edge on understory microclimatic parameters (temperature, relative humidity and Photosynthetically Active Radiation – PAR-).

FIGURE LEGENDS

FIGURE 5-1. Relative location of study sites. Location of transects at each site is shown in white triangles.
FIGURE 5-2. Design of the parallel transects and 50 x 60 m plots established at each forest edge at each site to study edge influence. Each transect allowed to perform surveys at several intercepts of the transects. Two contiguous parallel transects were established in order to include more sampling effort for each transect intercept.

FIGURE 5-3. Variation in forest structure parameters (canopy % gap fraction, fraction of Intercepted PAR – FiPAR-, % canopy openness and Plant Area Index) with distance from the forest edge.

FIGURE 5-4. Variation in understory microclimatic parameters (temperature, relative humidity and Photosynthetically Active Radiation – PAR-) with distance from the forest edge. .

FIGURE 5-5. Three dimensional (3D) scatterplot showing the distribution of understory microclimatic parameters (temperature, relative humidity and Photosynthetically Active Radiation – PAR-) as a function of distance from the forest edge.

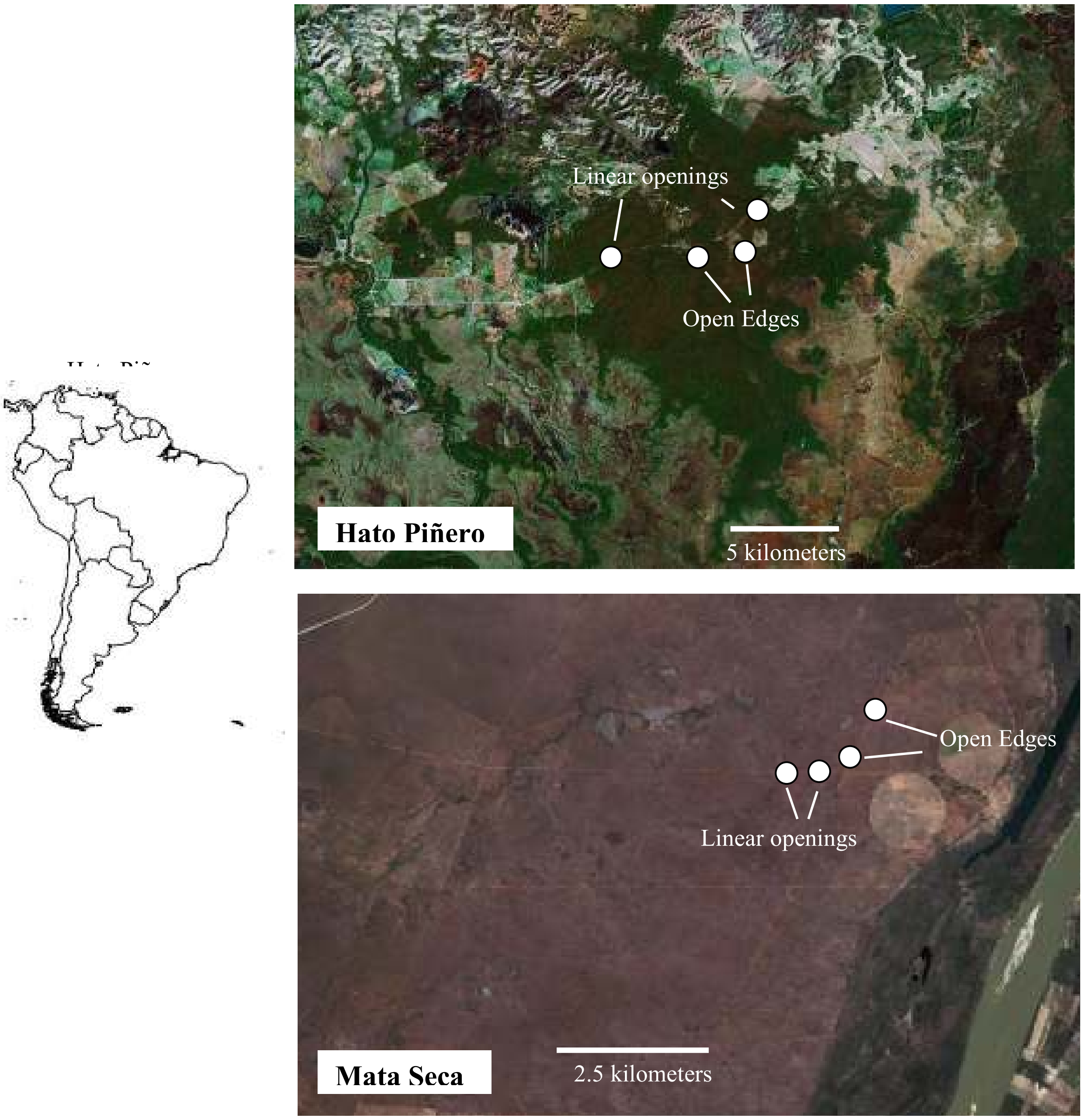
(Table 5-1)

	Site/Treatment		***P-value***
Gap Fraction	MS-Open pasture	$F_{2,7}$= 6.572	**<0.05**
	MS-Linear Openings	$F_{2,7}$= 21.131	**<0.05**
	HP-Open Pasture	$F_{2,7}$= 0.764	>0.05
	HP- Linear Openings	$F_{2,7}$= 0.844	>0.05
FiPAR	MS-Open pasture	***H***= 34.37	**<0.001**
	MS-Linear Openings	***H***= 4.906	>0.05
	HP-Open Pasture	***H***= 11.351	**<0.05**
	HP- Linear Openings	***H***= 6.894	**<0.05**
Canopy Openness	MS-Open pasture	***H***= 0.125	>0.05
	MS-Linear Openings	***H***= 27.291	**<0.001**
	HP-Open Pasture	***H***= 0.458	>0.05
	HP- Linear Openings	***H***= 10.131	**<0.05**
PAI	MS-Open pasture	***H***= 0.305	**<0.05**
	MS-Linear Openings	***H***= 22.018	**<0.001**
	HP-Open Pasture	***H***= 1.181	>0.05
	HP- Linear Openings	$F_{2,101}$= 4.059	**<0.05**

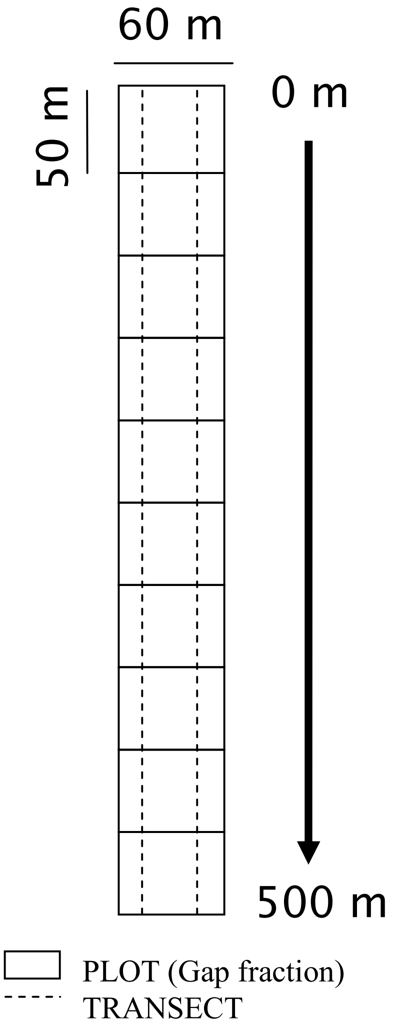
(Table 5-2)

	Hato Piñero site		
Distance from edge	*Median*	ANOVA *H*	*p-value*
PAR (µmols/m^2/sec)			
0-10 m	21.2	2425.733	<0.001
12-30 m	36.2		
50-100 m	46.2		
Relative Humidity (%)			
0-10 m	88.25	1062.483	<0.001
12-30 m	88.75		
50-100 m	84.25		
Temperature (°C)			
0-10 m	25.56	5817.269	<0.001
12-30 m	25.95		
50-100 m	26.925		
	Mata Seca Site		
Distance from edge	*Median*	ANOVA *H*	p-value
PAR (µmols/m^2/sec)			
0-10 m	58.7	961.059	<0.001
12-30 m	76.2		
50-100 m	91.2		
Relative Humidity (%)			
0-10 m	70.75	1286.84	<0.001
12-30 m	68.25		
50-100 m	68.25		
Temperature (°C)			
0-10 m	24.79	2890.868	<0.001
12-30 m	25.17		
50-100 m	27.12		

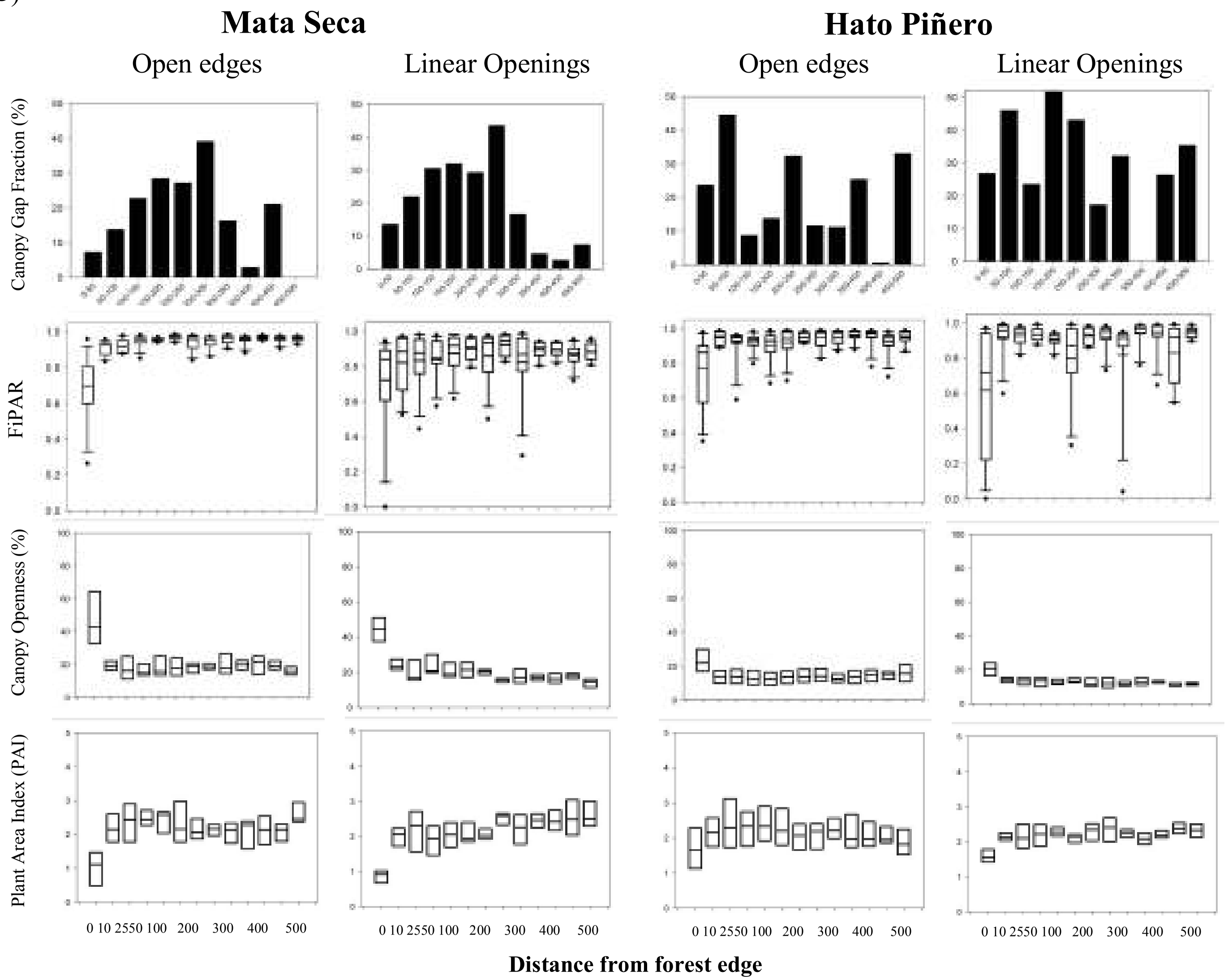
(Figure 5-1)


Linear openings
Open Edges
Hato Piñero
5 kilometers
Open Edges
Linear openings
Mata Seca
2.5 kilometers

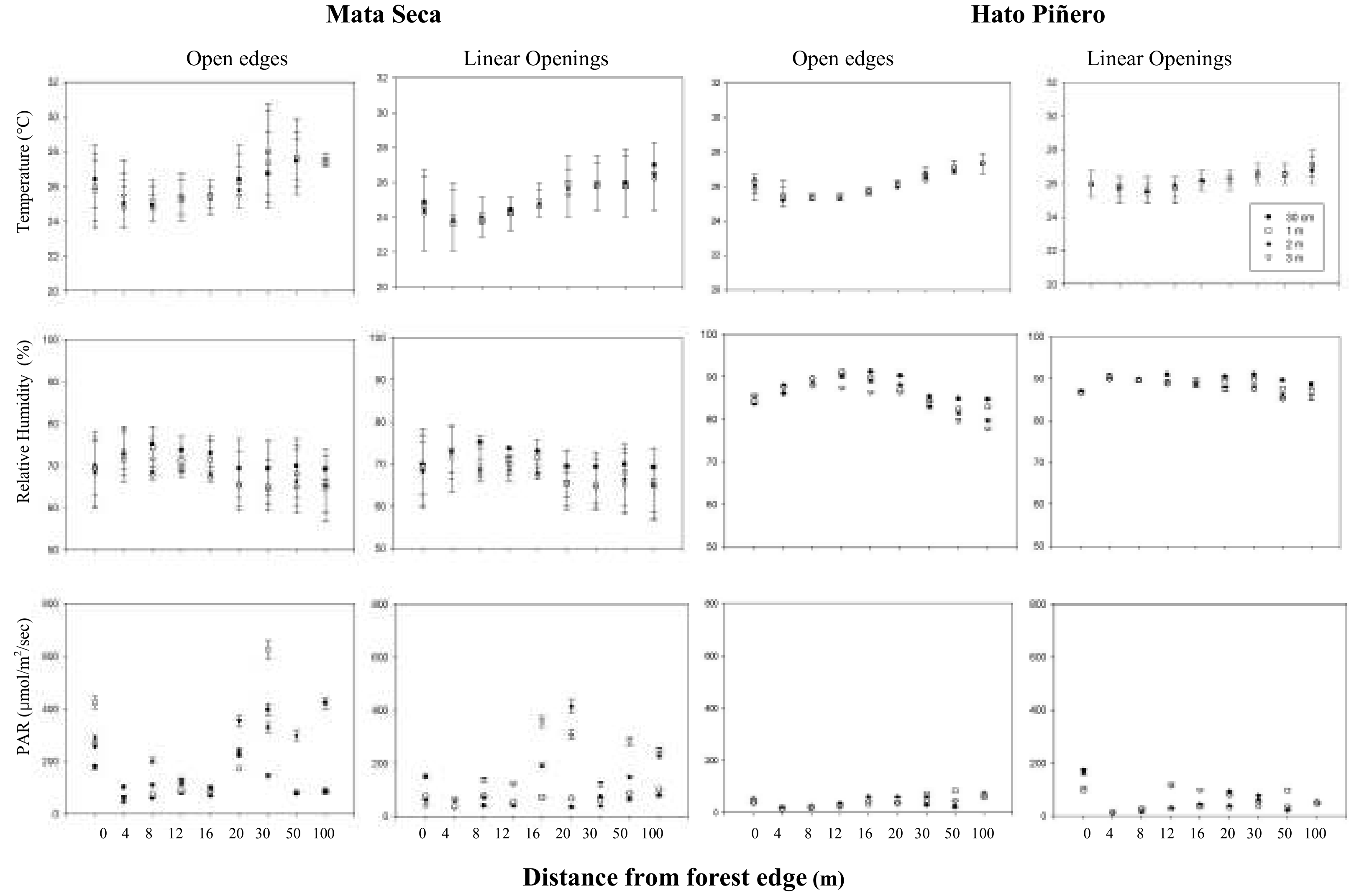
(Figure 5-2)



(Figure 5-3)

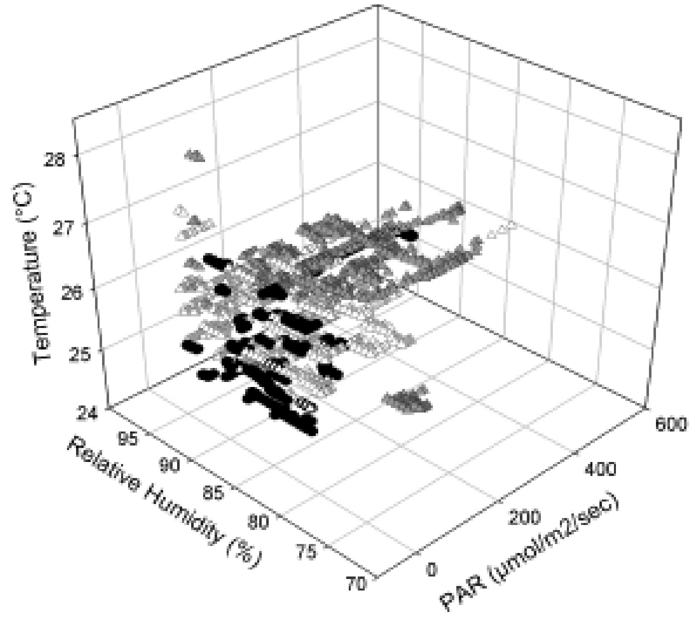

Mata Seca
Hato Piñero
Open edges
Linear Openings
Open edges
Linear Openings
Canopy Gap Fraction (%)
FiPAR
Canopy Openness (%)
Plant Area Index (PAI)
0 10 2550 100 200 300 400 500
Distance from forest edge

(Figure 5-4)


Mata Seca
Hato Piñero
Open edges
Linear Openings
Open edges
Linear Openings
Temperature (°C)
Relative Humidity (%)
PAR (µmol/m²/sec)
20
22
24
26
28
30
32
50
60
70
80
90
100
0
200
400
600
800
30 cm
1 m
2 m
3 m
0
4
8
12
16
20
30
50
100
Distance from forest edge (m)

(Figure 5-5)

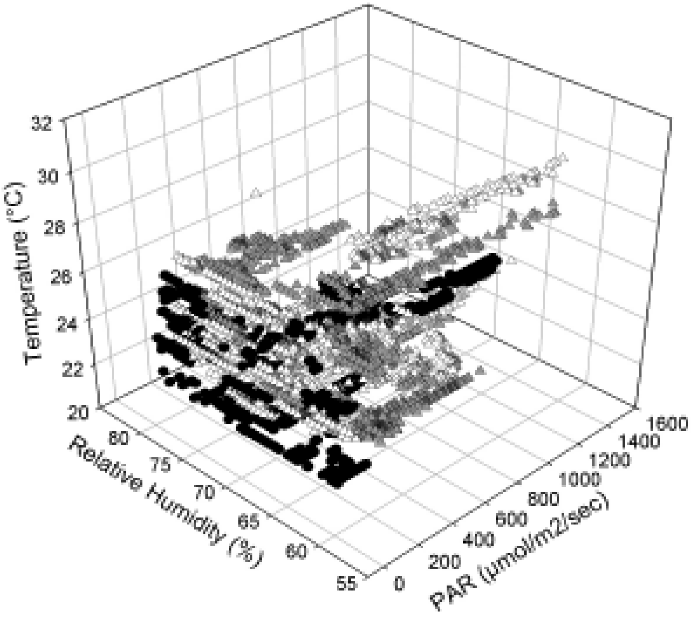
Hato Piñero – All transects



Mata Seca – All transects

Distance from forest edge

● 0-10 m
△ 12-30 m
▲ 50-100 m



LITERATURE CITED

Achard, F., H. D. Eva, H.-J. Stibig, P. Mayaux, J. Gallergo, T. Richards, and J.-P. Malingreau. 2002. Determination of deforestation rates of the world's humid tropical forests. Science 297 (5583): 999-1002

Aizen, M.; P. Feisinger. 1994. Forest fragmentation, pollination and plant reproduction in a Chaco Dry Forest, Argentina. Ecology 75(2):330-351.

Alves, R. 2008. Zonamento ambiental e os desafios da implementação do Parque Estadual Mata Seca, Municipio de Manga, Norte de Minas Gerais. Instituto de geociencias da Universidade Federal de Minas Gerais. Belo Horizonte, Brasil.

Asquith, N.; M. Mejia-Chang. 2005. Mammals, edge effects and the loss of tropical forest diversity. Ecology, 86(2):379-390

Bertsch C. & G. Barreto. 2008. Diet of the Yellow-knobbed curassow in the central Venezuelan Llanos. The Wilson Journal of Ornithology 120(4):767-777.

Bierregard R.; T. Lovejoy; V. Kapos; A. Dos Santos; R. Hutchings. 1992. The Biological dynamics of Tropical Rain Forest Fragments. BioScience 42(11):859-866.

Chaves, O.; G. Avalos. 2008. Do seasonal changes in light availability influence the inverse lefing phenology of the neotropical dry forest understory shrub *Bonellia nervosa?* Rev. Biol.Trop. 56(1):257-268.

Chazdon, R.; N. Fetcher. 1984. Photosynthetic Light environments in a lowland tropical rainforest in Costa Rica. Journal of Ecology 72:553-564.

Chong, M. M., K. Dutchak, J. Gamon, Y. Huang, M. Kalácska, D. Lawrence, C. Portillo, J. P. Rodríguez y A. Sánchez-Azofeifa. 2008. Remote Sensing. Páginas 47-80 En: J. M. Nassar, J. P. Rodríguez, A. Sánchez-Azofeifa, T. Garvin; M. Quesada, editores. Manual of Methods: Human, Ecological and Biophysical Dimensions of Tropical Dry Forests. Ediciones IVIC, Instituto Venezolano de Investigaciones Científicas (IVIC), Caracas, Venezuela.

Didham, R and Lawton, J. (1999) Edge structure determines the magnitude of changes in microclimate and vegetation structure in tropical forest fragments. Biotropica 31(1):17-30

Fuentes-Montemayor, E.; A. Cuaron; E. Vasquez-Dominguez, J. Benitez-Malvido; D. Valenzuela-Galvan; E. Andersen. 2009. Living on the Edge: roads and edge effects on small mammal populations. Journal of Animal Ecology 78:857-865.

Gamon J.; K. Kitajima; Mulkey S.; Serrano L. and Wright J. 2005. Diverse Optical and Photosynthetic properties in a Neotropical Dry Forest during the dry season: Implication for Remote estimation of photosynthesis. Biotropica 37(4):547-560.

Gelhausen S.; Schwartz, M.W. and Augspurger, C.K. 2000. Vegetation and microclimatic edge effects in two mixed mesophytic forest fragments. Plant Ecology 147:21-35.

Gerwing, J. 2002. Degradation of forests through logging and fire in the eastern brazilian amazon. Forest Ecology and Management 157, 131-141

Harper, K., S.E. MacDonald, P.J. Burton, J. Chen, K. Brosofske, S. Saunders, E. Euskirchen, D. Roberts, M. Jaiteh, P. Essen. 2005. Edge Influence on Forest Structure and Composition in Fragmented Landscape. Conservation Biology, Vol. 19 (3): 768-782
Jose, S., Gillespie, A., George S.J., and Kumar , B.M. (1996) Vegetation responses along edge-to-interior gradients in a high altitude tropical forest in peninsular India. Forest Ecology and Management 87 (1-3): 51-62.

Kalacska, M., Sanchez-Azofeifa, G.A., Calvo-Alvarado, J.C., Rivard, B., Quesada, M. 2005. Effects of Season and Successional Stage on Leaf Area Index and Spectral Vegetation Indices in Three Mesoamerican Tropical Dry Forests. Biotropica 37 (4): 486-496

Kapos, V., E. Wandelli, J.L. Camargo; G. Ganade. 1997. Edge-related changes in Environment and Plant responses due to forest fragmentation in Central Amazonia. Pages: 33-44, in Laurance, W. and Bierregaard, R. eds. 1997. Tropical Forest remnants: ecology , management and Conservation of Fragmented communities. The University of Chicago Press, USA. P. 612

Laurance W. 1997. Hyperdisturbed parks: Edge effects and the Ecology of Isolated Rainforest Reserves in Tropical Australia; Pages71-83; in Laurance, W. and Bierregaard, R. eds. (1997) Tropical Forest remnants: ecology , management and Conservation of Fragmented communities. The University of Chicago Press, USA. P. 612

Laurance W.; L. Ferreira; R. De-Merona, S. Laurance. 1998. Rain forest fragmentation and the dynamics of Amazonian tree communities. Ecology 79(6):2032-2040.

Laurance W., T.E. Lovejoy, H.L. Vasconcelos, E.M. Bruna, R. K. Didham, P.C. Stouffer, C. Gascon, R. O. Bierregaard, S. G. Laurance, E. Sampaio. 2002. Ecosystem decay of Amazonian forest fragments: a 22-year investigation. Conserv. Biol. 16: 605–618

Laurance, S. 2004. Responses of understory rain forest birds to road edges in Central Amazonia. Ecological Applications 14(5):1344-1357.

Laurance, W.; T. Curran. 2008. Impacts of wind disturbance on fragmented tropical forests: A review and synthesis. Austral Ecology 33: 399-408.

Licor Inc. (2010) Li-191SA Line Quantum Sensor Brochure. Licor Environmental Division. Lincoln, NE. USA. Available at http://www.licor.com/env/PDF/191sa.pdf

Manu S.; W. Peach; W. Cresswell. 2007. The effects of edge, fragment size and degree of isolation on avian species richness in highly fragmented forest in West Africa. Ibis 149: 287-297.

Miles, L., A. Newton, R. DeFries, C. Ravilious, I. May, S. Blyth, V. Kapos, J. Gordon. 2006. A global overview of the conservation status of tropical dry forests. Journal of Biogeography. 33, 491-505.

Murcia, C. 1995. Edge effects in fragmented forests: implications for conservation. Trends in Ecology and Evolution 10: 58-62

Murphy, P.G., A.E. Lugo. 1986. Ecology of tropical dry forest. Ann. Rev. Ecol. Syst. 17, 67–88.

Olofsson P., L. Eklundh, F. Lagergren, P. Jonsson; A. Lindroth. 2007. Estimating net primary production for Scandinavian forests using data from Terra/MODIS. Advances in Space research 39:125-130.

Pennington, T; G. Lewis; J. Ratter. 2006. Neotropical savannas and seasonnally Dry Forests: Plant diversity, Biogeography and Conservation. CRC Press, FL.USA.

Pohlman, C.L., S.M. Turton, M. Goosem. 2007. Edge effects of Linear Canopy Openings on Tropical Rain Forest Understory Microclimate. Biotropica 39 (1): 62-71.

Portillo C. & Sanchez A. (2010) Extent and Conservation of tropical dry forests in the Americas. Biological Conservation 143:144-155.

Quesada, M. G. A. Sanchez-Azofeifa, M. Alvarez-Anorve, K. E. Stoner, L. Avila-Cabadilla, J. Calvo-Alvarado, A. Castillo, M. M. Espirito-Santo, M. Fagundes, Geraldo W. Fernandes, J. Gamon, M. Lopezaraiza-Mikel, D. Lawrence, P. Morellato, J. S. Powers, F. S. Neves, V. Rosas-Guerrero, R. Sayago, G. Sanchez-Montoya (2009).Succession and Management of tropical dry forests in the Americas: Review and new perspectivas. Forest Ecology and Management. 258: 1014-1024.

Runkle, J. 1992. Guidelines and sample protocol for sampling forest gaps. USDA For. Serv. Gen. Tech. Rep. PNW-GTR-283.

Segura, G.; P. Balvanera; E. Duran; A. Perez. 2003. Tree community structure and stem mortality along a water availability gradient in a Mexican tropical dry forest. Plant Ecology 169:259-271.

Serbin S., S. Gower; D. Ahl. 2009. Canopy Dynamics and phenology of a boreal spruce wildfire chronosequence. Agricultural and Forest Meteorology 149: 187-204.

Skole, D.; C. Tucker. 1993. Tropical deforestation and Habitat Fragmentation in the Amazon: satellite Data from 1978 to 1988. Science 260 (5116):1905-1910.

Sizer, N.; E. Tanner. 1999. Responses of woody plant seedlings to edge formation in a lowland tropical rainforest, Amazonia. Biological Conservation 91: 135-142

Souza Jr. C., Roberts, D.A, Cochrane, M. 2005. Combining spectral and spatial information to map canopy damage from selective logging of forests fires. Remote sensing of environment 98, 329-343.

Turton S. and Freiburguer, H.J. 1997. Edge and Aspect effects on the Microclimate of a Small Tropical Forest remnant on the Atherton Tableland, Northeastern Australia. Pages 45-54. in Laurance, W. and Bierregaard, R. eds. 1997. Tropical Forest remnants: ecology , management and Conservation of Fragmented communities. The University of Chicago Press, USA. P. 612

CHAPTER 6 - Remote Sensing of edge effects in dry forest fragments using Chris /Proba Imagery

INTRODUCTION

One of the major changes brought about by habitat fragmentation to tropical forests is an increase in the proportion of edge exposed to other habitats (Kapos et al. 1997, Laurance & Curran, 2008). Near fragment edges, abrupt exposure to different environmental conditions alters microclimate and as a result, increments in tree mortality rates and decreases in plant species recruitment affect vegetation dynamics (Asquith & Mejia-Chang, 2005, Laurance et al.1998.). Direct effects include changes in air temperature, soil moisture, relative humidity and the amount of light penetrating to the forest understory (Kapos et al. 1997; Pohlman et al. 2006). Typical vegetation responses to these changes in edge environment result in an increased presence of exotic and disturbance-adapted species, increased sapling and tree densities, increased shrub cover, and higher species richness (Gelhausen et al. 2000; Harper et al. 2005, Laurance et al. 2002). Moreover, increased lateral windthrow make treefall gaps more frequent near the edges of a forest fragment (Kapos et al. 1997, Laurance & Curran, 2008).

Inferring or directly quantifying the amount of forest affected by edge effects in a fragmented landscape is important in order to understand the degree of disturbance of a particular ecosystem, as well as the spatial distribution of its ecological processes and species abundance at the landscape level. However, very little information exists regarding attempts to efficiently infer or model edge effects at the landscape level in a particular ecosystem. For example, Skole & Tucker (2003) estimated that the area affected by edge effects approximated to 588,000 km^2 for the Brazilian Amazon alone, These estimates were drawn from the assumption (supported by literature) that edge effects penetrate up to 1 km into the forest in all edges of the forest fragments evaluated. Inversely, Laurance & Yensen (1991) developed a mathematical model to predict the core area of fragments (forest interior not affected by edge effects). This study was based on approximate assumptions on the effect of fragment size and shape on the penetration of edge influence and has also been used as reference for predicting habitat vulnerability to disturbance using geographic information systems (Rodriguez et al. 2007). Such studies assume that edge effects are symmetrical around the perimeter of a fragment. Other authors (such as Malcolm et al. 1994, Zhen & Chen, 2000) have stressed out that edge effects are in fact non-symmetrical and that different edges in the same fragment are exposed to different environmental conditions and matrices. Therefore, modeling techniques such as those applied by Skole & Tucker (2003) and Laurance & Yensen (1991) do not show realistic spatial patterns of edge effects across the landscape. A more realistic multivariate approach is needed. Such approach should be able to show spatial variations of the severity and distribution of edge effects within a forest fragment.

In this context, Malcolm et al. (1994) developed a predictive model of edge effects that takes into account additive effects from different edges of the fragment that increase the total area affected. Zheng & Chen (2000) developed a more complex, spatially-explicit, generic model for delineating area of edge influence within a real landscape by combining remote sensing, geographic information systems and computer programming techniques. Their work incorporated key parameters such as land cover type, edge orientation, edge contrast, topography, prevailing directions of edge effects, among others, in a model to map potential edges around forests. Zheng & Chen (2000) model included several critical features that were lacking in traditional approaches so results could be considered more realistic, however, their approach was dependant on abundant field information available from a particular study site. The models carried along an important number of assumptions for any edge effect predicted which can be impractical for the assessment of large fragmented forest areas.

A currently source of information that can be used to improve edge effect modeling is optical remote sensing. Optical remote sensors in orbit around the earth have been used to directly measure biophysical properties of tropical forest canopies (Kerr & Ostrovsky, 2003; Turner et al., 2003; Gillespie, 2008). Remotely-sensed spectral imagery can provide multitemporal spatially-explicit information from local to regional scales. It can provide spectral measurements for entire fragmented ecosystems that can be linked to ecosystem structure, function and processes. Spectral vegetation indices (SVIs) derived from spectral band ratios have been especially efficient in predicting tropical forest structural parameters such as leaf area index, primary productivity, fraction of intercepted photsynthetically active radiation (FiPAR) and species richness and composition (Gillespie et al. 2005; Phillips et al.2008; Kalacska et al. 2005, Gamon et al. 2005; Feeley et al. 2005, Oindo et al. 2002; Bailey et al. 2004).

Certainly, previous models have improved our ability to calculate edge effects for forest fragments at the landscape level. However, current remote sensing technology has the possibility of allowing us to directly detect canopy structural changes from the edge of the forest to the interior. This ability would improve predictive edge modelling, and could be used directly to quantify its magnitude and distance. In this study, we measured the changes in the fraction of intercepted photosynthetically active radiation (FiPAR) across four edge-to-interior transects in tropical dry forests fragments and investigated its correlation to SVIs computed from the CHRIS (Compact High Resolution Imaging Spectrometer) sensor on board of the Proba platform. The objective of the study is to provide a first evaluation of SVIs as potential predictors of edge influence on canopy structure in tropical dry forests and suggest proper techniques for its use and analysis.

METHODS

Study sites

Two tropical dry forest fragments were selected to conduct this study. One is located within the Parque Estadual da Mata Seca in Brazil, and the second within the Hato Piñero Private Wildlife Refuge in northern Venezuela (See Figure 6-1). Both fragments represent remnants of mature tropical dry forests within agricultural and cattle ranching land use matrices. In Figure 6-2, I show the time period when the field data was collected in contrast with monthly precipitation and vegetation phenology for the years 2007 and 2008 at each site. Global rainfall data is available from the Tropical Rainfall Measuring Mission - TRMM - (at http://trmm.gsfc.nasa.gov/). Continuous bi-monthly MODIS Enhanced-Vegetation Index data was acquired from the NASA´s Distributed Active Archive Center (http://daac.ornl.gov/MODIS/). As shown, field and remotely-sensed spectral measurements at each site were made during the wet season (Between May and June 2007 for Hato Piñero and between December 2007 and January 2008 for the Mata Seca site), when there were fully-expanded canopy leaves.

Parque Estadual da Mata Seca, Minas Gerais, Brazil (MS site)

The Parque Estadual da Mata Seca is a provincial conservation unit located along the border of northern Minas Gerais state and south-western Bahia state in Brazil and is centered at 14°50'50"S and 43°58'43"W. The region is mainly surrounded by agricultural lands and highly fragmented remnants of dry forest within the Atlantic Dry Forest and the Caatinga ecoregion of eastern Brazil. The Parque Estadual Da Mata Seca was created in the year 2000 in order to preserve important remnants of diverse vegetation formations such as tropical deciduous forests, riparian forests and "Furados" or open arboreal caatinga. Tropical Dry forests are found where eutrophic soils of calcareous origin favor the development of a tall deciduous vegetation (Alves, 2008). The site has a mean annual temperature of 24º and an annual rainfall is 916 mm and highly seasonal. The dry season extends for almost 7 months from May until November, while most of the rainfall concentrates between November and April (Alves, 2008). The forest fragment studied is located at the center of the site and is surrounded by a secondary dry forests, open pastures and agricultural land.

Hato Piñero, Cojedes State, Venezuela (HP site)

The Hato Piñero is a private cattle ranch situated in the Central Venezuelan Llanos in Cojedes State (8°52'45"N, 68° 9'10"W). The site is a mosaic of pastures, savannas, dry forests and gallery forests. Average annual temperature and precipitation is 27.5°C and 1,469.6 mm, respectively; and a strong seasonality with a rainy season occurring from April to November and a dry season from December to March (Bertsch & Barreto, 2008). The forest fragment studied is located in the center of the ranch occupying approximately 30,000 ha. These forests are medium tall (25-30 m), semi-deciduous or deciduous, with almost all its southern half subjected to flooding in the rainy season. The site has been established as a private conservation unit since 1953 with limited selective logging, no wildlife hunting, fire control and protection of dry forest remnants. In 2005, the Venezuelan National Land Institute, under a land reform campaign that aims to break up large landholdings to distribute among farmers, announced the confiscation of Hato Piñero and all its assets (http://www.branger.com).

Fraction of Intercepted Photosynthetically Active Radiation (FiPAR)

The fraction of intercepted photosynthetically active radiation (FiPAR) represents the amount of incident photosynthetic photon flux density (PPFD) that is absorbed by the forest canopy (Gamon et al. 2005). FiPAR is measured by contrasting below canopy downwelling PAR readings to above canopy downwelling PAR readings. FIPAR is calculated using the formula [(Id A- Id B)/Id A] , where Id A represents downwelling PAR radiation above the canopy, and Id B represents downwelling PAR radiation below the canopy.

We established 500 m transects from the edge of the fragment into the forest interior in four locations at each site. Each transect was surveyed at several intercepts of the fraction of intercepted photosynthetically active radiation (FiPAR) by the forest canopy. We established two contiguous parallel transects at each location in order to include more sampling effort for each transect intercept. Forest area surveyed at each location covered 0,03 km^2. For each site, one transect was located in edges exposed to linear openings (unpaved roads approximately 10 m wide), and one transect was located in edges facing open pastures (large forest clearings with little to no forest vegetation regrowth) in order to include exposure to different conditions at the matrix. Transect selection was made regarding effects of edge aspect and exposure to prevailing wind and solar radiation conditions could not be assessed because of limited amount of comparable edges on mature dry forest. In order to measure FiPAR, transects were surveyed at 13 line intercepts located at 0, 10, 25, 50, 100, 150, 200, 250, 300, 350, 400, 450, and 500 m from the edge of the forest. At each line intercept, we used a Li-190 Line Quantum Sensor (LI-COR Biosciences) to measure Id B at the intercept, and at 7.5 m from the intercept (left and right). Measurements were made at breast height. Id A was monitored on a large clearing outside the forest using a PAR sensor (LI-COR Biosciences) connected to a Hobo data logging weather station (Onset Computer Corporation). FiPAR values from 0 to 50 were grouped and averaged in order to represent FiPAR at the edge of the forest. Figure 6-2 illustrates the field sampling design for FiPAR.

CHRIS/Proba imagery

For the collection of remotely-sensed spectral observations, we used spectral reflectance data from the Compact High Resolution Imaging Spectrometer (CHRIS) on board of the PROBA-1 satellite. This sensor acquires high spatial resolution (17-20 m or 34-40 m) images of Earth's surface in up to 62 narrow spectral channels located in the visible and near infra-red wavelengths (Barnsley et al. 2004). CHRIS measures spectral reflectance in the visible/near infrared (NIR) bands from 400-1050 nm, with a minimum spectral sampling interval ranging between 1.25 (at 400 nm) and 11 nm at 1000 nm (Guanter et al. 2005). CHRIS Level 1A products include five formal CHRIS imaging modes, classified as modes 1 to 5. For this study, CHRIS MODE-4 Chlorophyll band set was used, which provides spectral measurements from 489 nm to 792 nm (a total of 18 bands) using a minimum sampling size (pixel size) of 17 x 17 m.

For Mata Seca, cloud free imagery was available for the wet season in 2008, approximately one month after the field data collection campaign took place (02/24/2008). For Hato Piñero, cloud free images were available for the transition between the wet season and dry season in 2007 (12/01/2007), approximately six months after field data collection. Since there was no indication that important forest biomass changes occurred (such as deforestation events or the formation of new large tree fall gaps) between the field data collection dates and imagery acquisition dates, we assumed that the variations in canopy structure as registered by FiPAR values in all transects were the same at the time the image was acquired.

Furthermore, as seen in Figure 6-2, the image acquired for MS records the spectral response of the dry forest when canopy leaves are fully expanded. In contrast, the image acquired for HP contains spectral information when the forest canopy has most likely shredded a percentage of its leaves. Interestingly, previous studies have found that the use of imagery collected during the dry season is able to enhance dry forest structural properties and improve its mapping (Kalacska et al. 2007). Therefore, this difference allowed us to explore the potential of dry and wet season imagery for modeling edge effects.

Another important aspect for imagery selection was the angle of observation or view angle used. For any location, the CHRIS sensor provides multi-angular images at +/-55°, +/-36° and 0° or Nadir (Shaker et al. 2008). However, images at different angles are separately acquired by the sensor. Alonso and Moreno (2005) showed that orbital assumptions for acquiring data at different angles affect the location of the scanned area. For this reason, images provided by the sensor do not share the same spatial coverage or image dimensions. In our case, with the exception of the images acquired at an angle of observation of -36°, no other requested images of any angle was able to cover all sites and transects sampled in the ground. Therefore, for our analyses, we used CHRIS imagery acquired at a view angle of -36°. Using this angle, we were able to extract spectral values for four transects surveyed in the field.

Although viewing geometry is a major determinant controlling the spectral behavior of vegetation canopies, Verrelst et al. (2008) showed that at this specific angle (-36°), spectral vegetation index values derived from CHRIS sensor over forest canopies do not significantly differ from nadir values. In order to corroborate this, a complementary evaluation of the effect of the view angle on the correlation between the two variables was performed. Noise reduction and atmospheric correction was achieved for each CHRIS image using the BEAM Version 4.6 developed by the European Space Agency (ESA).

Spectral Vegetation Indices (SVIs)

Vegetation biophysical variables have been extensively studied and correlated to radiometric vegetation indices derived from satellite platforms sensors (Jensen, 2007). These indices, which are derived from reflectance in the red and near infrared regions of the spectrum provide an estimate of green canopy display and thus, potential photosynthetic activity (Gamon et al. 2005). SVIs at the canopy level have been related to canopy structure (Kerr & Ostrovsky, 2003; Kalacska et al. 2005), species composition (Gillespie et al. 2005) and ecosystem function (Chong et al. 2003). Two widely used indices are the normalized difference vegetation index (NDVI) and the simple ratio (SR):

$$\mathrm{NDVI}= (R_{NIR} - R_{red}) / (R_{NIR} + R_{red})$$

and

$$\mathrm{SR}= R_{NIR} / R_{RED}$$

where the R_{NIR} and the R_{red} indicate reflectance in the near-infrared and red wavebands. We transformed each acquired image to NDVI and SR using narrow band reflectances at 680 nm (Band C5; R_{red}) and 792 nm (Band C18; R_{NIR}). For the collection of SVIs, we identified the starting point of every transect at the forest edge using the field coordinates and high spatial resolution imagery available in Google Earth. We then extracted spectral values for every pixel from the starting point to approximately 500-m into the forest interior perpendicularly to the forest edge (30 pixels). For every pixel we also added the two adjacent pixels at both sides (90 pixels in total). Figure 2 illustrates the pixel sampling design compared to the field data.

Analysis

Statistical differences between FIPAR, NDVI and SR collected at each site were compared using t-tests and Mann-Whitney non-parametric tests (Gotelli & Ellison, 2004). For analyzing and comparing SVIs to FIPAR as a function of distance from edge, we extracted values from 3 x 3 pixel window averages from the forest edge to the forest interior. This transformation allowed to compare trends using ten values of SVI to ten values of FiPAR collected in the field. Using this dataset, we compared the relationship between SVIs and FiPAR collected in the ground by fitting the best model (linear or non-linear) that described the relationship between the two variables (SVI and FiPAR). For a complementary evaluation on the effect of the view angle, the transect that showed the best fit between SVIs and FiPAR, and that was also spectrally sampled by the CHRIS sensor at view angles of -36°, 0° and +36°, was selected. This information was used to investigate the correlation between the two variables at each view angle.

RESULTS

Results from the collection of FiPAR data in the field showed that both MS and HP sites differ in the amount of light absorbed by the forest canopy. At the MS site, FIPAR values remained high and ranged between 0.86 and 0.97 (mean = 0.94) while values at the HP site ranged between 0.68 and 0.95 (mean = 0.89). Overall, the HP site have significantly lower FIPAR than the MS site (Mann-Whitney U= 73; P= <0.001). Figure 6-4 shows these differences. In the MS open edge site, we observed a decrease of FIPAR values within the first 50 m from the edge and then values remained high and stable towards the interior. In the the MS linear opening site, we observe the same trend except for a slight decrease between 300-500 m from the edge that occurs as a product of a large canopy opening created by the fall of a >25 m tall of a *Cavallinesia arborea* tree. In the HP open edge site, FiPAR values were more abrupt and variable with slight decreases within 25 and 300 m from the edge as a result of the increase of the frequency of smaller tree fall gaps. In the MS linear opening site, more drastic interruptions of the canopy were evident at the edge and then at 150 m from the edge. There are also important decreases in canopy cover between 300-450 m from the edge that were recorded by FiPAR values. Overall, these results show that the HP sites have a more open and disturbed canopy.

Further statistical t-tests showed that NDVI and SR averaged values at a -36° view angle, were, indeed, significantly different between the MS and HP site (t= 22 for NDVI; t=36 for SR; both df = 38 and P=<0.001). NDVI values for the HP site ranged between 0.67 and 0.78 (mean = 0.73) while NDVI values for the MS site ranged between 0.87 and 0.90 (mean = 0.89). In the other hand, SR values for the HP site ranged between 5.1 and 8.2 (mean = 6.5) while SR values for the MS site ranged between 16.12 and 19.72 (mean = 18.23). However, these differences cannot be attributed to inherent forest structural or compositional characteristics between sites (as suggested by FiPAR values) but they should be attributed to the phenological status of the forest at each site. As seen in figure 6-2, imagery acquired for the HP site belonged to the transition between the wet and the dry season when the forest have shredded a percentage of its leaves, while the images acquired for MS belonged to the middle of the wet season when the canopy leaves were fully expanded.

Nonetheless, when comparing FiPAR values collected in the field to 3x3 pixel averaged SVIs values for each transect intercept, significant correlations linked to structural characteristics of the forest, especially at the HP site were found. Figure 6-5 shows FIPAR values plotted against SR and NDVI. At the MS site we observed a slight decrease of SVIs with lower FiPAR values, but no statistically significant correlation was found. The relative homogeneity that we found in canopy closure at both MS transects with no sudden drops in FiPAR, might have impeded the sensitivity of SVIs to changes in the canopy. In the other hand, at the HP site both NDVI and SR were strongly and significantly correlated to FiPAR values collected in the field (R=0.95, P<0.001 for SR and R=0.96, P<0.001 for NDVI). At this site, large canopy disturbances and/or interruptions caused mostly by tree fall gaps might have been amplified by the exposure of differences in the woody component and litterfall, as a result of the loss of canopy foliage during the transition between the wet and dry season (Kalacska et al 2007). Such structural features appeared to be detected by SVI values.

SVI values measured continuously from the edge to the forest interior from CHRIS/Proba spectral measurements at 17 x 17 m pixel resolution are shown in Figure 6-6. Each point records the mean value from three adjacent pixels. Although FIPAR values were not correlated to SVIs values at the MS site, values observed did capture the decrease of canopy cover in the first 150 m from the edge and show a correspondence to changes in FiPAR towards the interior from field measurements. Both SR and NDVI show similar trends along the edge at the MS site. Trends in SVIs values at the HP site were better captured, especially for the HP linear opening transect where variations in canopy cover (as registered through FiPAR) were markedly evidenced in NDVI values.

In order to show the correspondence between FiPAR and SVIs as a function of distance from forest edge, results in 3x3 pixel averaged values of NDVI to FIPAR values collected in the ground are shown, from the forest edge to the forest interior (Figure 6-7). The Y axis scales are modified for each individual transect plot in order to maximize contrast between variables. SVI values at: a) the MS open edge transect, b) the MS linear opening and c) the HP open edge transects, evidence some similarities to FiPAR but fail to show an overall strong and statistically significant correlation. However, the HP linear opening transect did showed a strong and significant correlation between the two variables (R= 0.95, P=<0.01). For the MS linear opening site, we observed that a decrease in NDVI values in the first 100 m from the edge resemble trends in FiPAR, and also at the 350-500 m from edge, but values at mid-distances are noticeably dissimilar. The same occurs for the HP open edge transect, were values up to 300 m from the edge capture most of the variations in FiPAR throughout the edge, but fewer similarities are found towards the forest interior. In general, we found that the HP linear opening and the MS open edge transects show the best correlation between NDVI and FiPAR as a function of distance from edge. Both transects show a correspondence between the two variables, although in the HP linear opening this trends are more pronounced. In general, we found that variations in FiPAR and canopy cover are captured by NDVI at the first 150 m from the edge in all transects and the ability of NDVI to detect variations towards the forest interior differ between transects.

Multi-angle observations

For a complementary evaluation on the effect of the view angle, I analyzed the relation between FiPAR and NDVI at the HP linear opening transect using multiangular data from CHRIS/Proba (See Figure 6-8). As shown in the previous analysis, NDVI collected at a -36° angle of observation was significantly correlated to FiPAR values (R = 0.97, P= <0.01). At this angle, NDVI values ranged between 0.67 and 0.74 (mean = 0.71). NDVI values at +36° angle of observation ranged between 0.68 and 0.76 (mean = 0.72) showing a correlation that was very close to significance to FiPAR (R = 0.73, P = 0.06). At a 0° angle of observation, NDVI values ranged between 0.69 to 0.79 (mean = 0.74) and show no statistically significant correlation to FIPAR (R = 0.68, P = 0.14). An improvement in the correlation between the two variables when using off-nadir spectral data at an angle of observation of -36° and +36°, might be explained by a possible exacerbation of canopy structural differences at different angles of observation as a consequence of the additive effect of sun and view angles on the red and near-infrared spectral values (Galvao et al. 2004; Asner & Warner, 2004).

DISCUSSION

Overall, results indicate that changes in FiPAR measurements collected from the field are correlated to SVIs derived from the CHRIS/Proba spectral bands and can potentially identify changes in canopy cover related to elevated frequency of treefall gaps near the edge, especially within the first 150 m from the forest edge. This relationship, however, was not found in all studied sites. Differences in forest phenology between sites may have played a major role defining this relationship. CHRIS Imagery for the HP site was acquired during the transition period between the wet and the dry season, while the images for MS were acquired in the middle of the wet season. As expected in the MS site, SVIs showed significantly higher values than in the HP site given that the canopies had fully expanded leaves at this time of the year. However, SVIs values were not correlated to FiPAR (Figure 6-5) and neither showed sensitivity to FiPAR variations along the edge transects in this site. For MS, a drop in SVIs values in the first 100-150 m was registered at all transects which was correspondent to lower FiPAR values at the same distances from the edge (see Figures 6-6 and 6-7). After this distance range, most variations shown by FiPAR values were not detected by SR or NDVI at the MS site. Variations in canopy cover might have been difficult to detect by the SR and NDVI since these indices reach saturation after a certain foliage density (Liang 2004).

In the HP site, SVIs showed significantly lower values than the MS site. Here, the CHRIS sensor recorded the spectral response of the dry forest when it had shredded a percentage of its canopy foliage. Kalacska et al. (2007) showed that dry forest structural properties are more pronounced during the dry season where differences in wood density and litterfall in the understory are distinguished. Figure 6-5 shows that values in NDVI and SR were strongly and significantly correlated to FiPAR. This relationship follows a non-linear behaviour where SVIs saturate after certain density in canopy foliage (Jensen 2007). When FiPAR was plotted against SVIs values as function of distance from the edge (Figure 6-7), variations in FiPAR caused by an increase in lateral light penetration and tree fall gap frequency, were closely detected by the HP linear opening transect but no for the HP open edge transect. As seen in Figure 6-4, the HP linear opening transect showed abrupt variations in canopy structure when sampled during the wet season. Spectral indices in the transition between the wet and dry season closely identified these variations.

In general, two main elements seem to control the ability of SVIs in responding to the increase of lateral light penetration and tree fall gap frequency. First, forest phenology might play a critical role in this relationship since variations in structural properties are better distinguished during the dry season. This might have been the key element that allowed detecting edge effects in canopy structure for the HP site, but not for the MS site. Secondly, the severity of disturbances in canopy cover as a result of edge effects that were found in the HP linear opening site could have exacerbated the structural changes detected by the SVIs. At this transect, we found the strongest and most significant correlation between NDVI and FiPAR (R=0.97, P<0.01). A better correspondence between SVIs and FiPAR as a function of distance to edge was also found in this transect.

Although the responses were very similar, we found slightly better correlations using NDVI than SR, however, there is no evidence that the use of any of these spectral indices affected the relationships to FiPAR as a function of distance from the forest edge. Finally, using multiangular spectral measurements from the CHRIS sensor from the HP linear opening transect, I found that the use of angles of observation of -36° and +36° improved the correlation between NDVI and FiPAR, and that the use of an angle of observation of 0° negatively affected this relationship. These results seem to differ from Verrelst et al (2008) where they show no significant differences between NDVI values at nadir and -36° in forest canopies using CHRIS imagery. An improvement in the correlations using off-nadir values might be related to the exacerbation of canopy structural differences as a consequence of the additive effect of sun and view angles on the red and near-infrared spectral values. The evaluation of the relationship between FiPAR and NDVI values collected at three different angles of observation indicate that off-nadir spectral data might be critical for identifying trends in canopy cover across tropical forest edges.

No studies before have addressed the ability of optical remote sensing to detect and model biophysical disturbances caused by edge effects in tropical forests. Previous work by Malcolm et al. (1994) and Zheng & Chen (2000) have attempted to model the distribution of edge effects in landscapes through multivariate predictive modeling. Although these models can help inferring ecosystem damage from edge effects, these do not represent the true response of the forest. In the other hand, spectral measurements from airborne or spaceborne spectrometers are sensitive to changes in the biophysical structure of the forests (Kerr & Ostrovsky 2003, Kalacska et al. 2005, Asner et al. 2009). Therefore, this work represents a first look to the possibility of modeling the spatial distribution of edge effects in tropical forest landscapes using remote sensing.

CONCLUSIONS

Following the fragmentation of a continuous forest fragment, exposure to edges facing open pastures or roads suffer direct effects such as physical damage, changes in productivity, evapotranspiration, canopy cover, tree density and overall biomass, frequency of debris, nutrient cycling, decomposition, canopy cover, air temperature, soil moisture, relative humidity and the amount of light penetration to the forest understory (Harper et al. 2005; Laurance et al. 2002, Kapos et al. 2007; Pohlman et al. 2006). Changes in species composition and an increase in liana abundance are also characteristics responses to edge creation (Laurance et al. 2002). Edge influence on tropical forest fragments is an important source of disturbance to the conditions and stability of ecological functions within these fragments. Our ability to identify, quantify and predict the occurrence and the magnitude of these disturbance factors will allow conservation practitioners to develop proper strategies for tropical forest management and reserve design. Previous efforts on determining the extent of edge effects in tropical forest fragments have been carried out using theoretical approximations derived from field data that, to improve approximations, incorporate parameters such as edge orientation, edge contrast, topography, prevailing directions of edge effects, among others. The objective of this study was to provide an initial evaluation of SVIs derived from space-borne optical remote sensing as potential predictors of edge influence on canopy structure in tropical dry forests.

The results show that SVI values can be used as a direct indicator of changes in canopy structure and photosynthetic light absoption or as inputs to more complex models that include various parameters. However, results also show that, in order to detect edge effects from remote sensing in tropical dry forest fragments, three main aspects need to be taken into consideration: forest phenology, severity of edge effects and the view angle of spectral data. These three factors appear to be critical in order to find significant correlations between SVIs and FiPAR in tropical dry forest edges. Such factors help exacerbating changes in forest canopy and understory properties related to edge effects. Other spectral analysis techniques might also be useful in detecting forest structural and even, compositional gradients from the forest edge. Recent advances in the analysis of spectral information derived from space-borne and air-borne sensors have improved our ability to detect and model ecosystem function and biochemical properties, as well as species composition and liana abundance (Carlson et al. 2007, Asner et al. 2009; Kalacska et al. 2007). Therefore, future experiments or studies can also be designed to identify compositional and biochemical changes related to edge effects in tropical forests. Increments in the frequency of treefall gaps near the edges could also be evaluated using shadow-fraction or soil-fraction products from red and near-infrared wavelengths since these have proved to be good predictors of top-of-canopy biophysical structure (Asner et al. 2003).

One of the limitations to this study is the use of a single variable collected at the field as an indicator of changes at the edge. Future field collection research should be directed towards the evaluation of edge gradients on species composition and species diversity, liana abundance, leaf area index, biomass and biochemical heterogeneity. Also, future studies should evaluate the ability of several multispectral and hyperspectral sensors, at different spatial resolutions, and angles of observations, to detect forest disturbances at the edge. Such studies should also consider assessing the distribution of edge disturbances for an entire tropical forest fragment using optical remote sensing techniques, in order to evaluate the possibility of discriminating the core-area of the fragment to the area affected by edge effects.

FIGURE LEGENDS

FIGURE 6-1. Relative location of study sites. Location of transects at each site is shown in triangles.

FIGURE 6-2 MODIS 16-Day enhanced Vegetation Index (EVI) and rainfall data for Hato Piñero and Mata Seca during the years 2007 and 2008. The figures indicate the forest phenological status (vegetation greenness index measured every 16-days) and average monthly precipitation for the field data collection dates and the image acquisition dates.

FIGURE 6-3. Design of the transects established at each forest edge at each site to study edge influence. Each transect allowed to perform surveys at several intercepts of the transects. Two contiguous parallel transects were established in order to include more sampling effort for each transect intercept. Squared grid shows the approximate location of CHRIS/Proba pixels in relation to the transects.

FIGURE 6-4. Variation of the Fraction of Intercepted Photosynthetically Active Radiation (FiPAR) with distance from the forest edge across study sites. For each site, one transect was located in edges exposed to linear openings, and one transect was located in edges facing open pastures. Transects were surveyed at 13 line intercepts from the edge of the forest. At each line intercept, we used a Li-190 Line Quantum Sensor (LI-COR Biosciences) to measure Id B at the intercept, and at 7.5 m from the intercept (left and right).

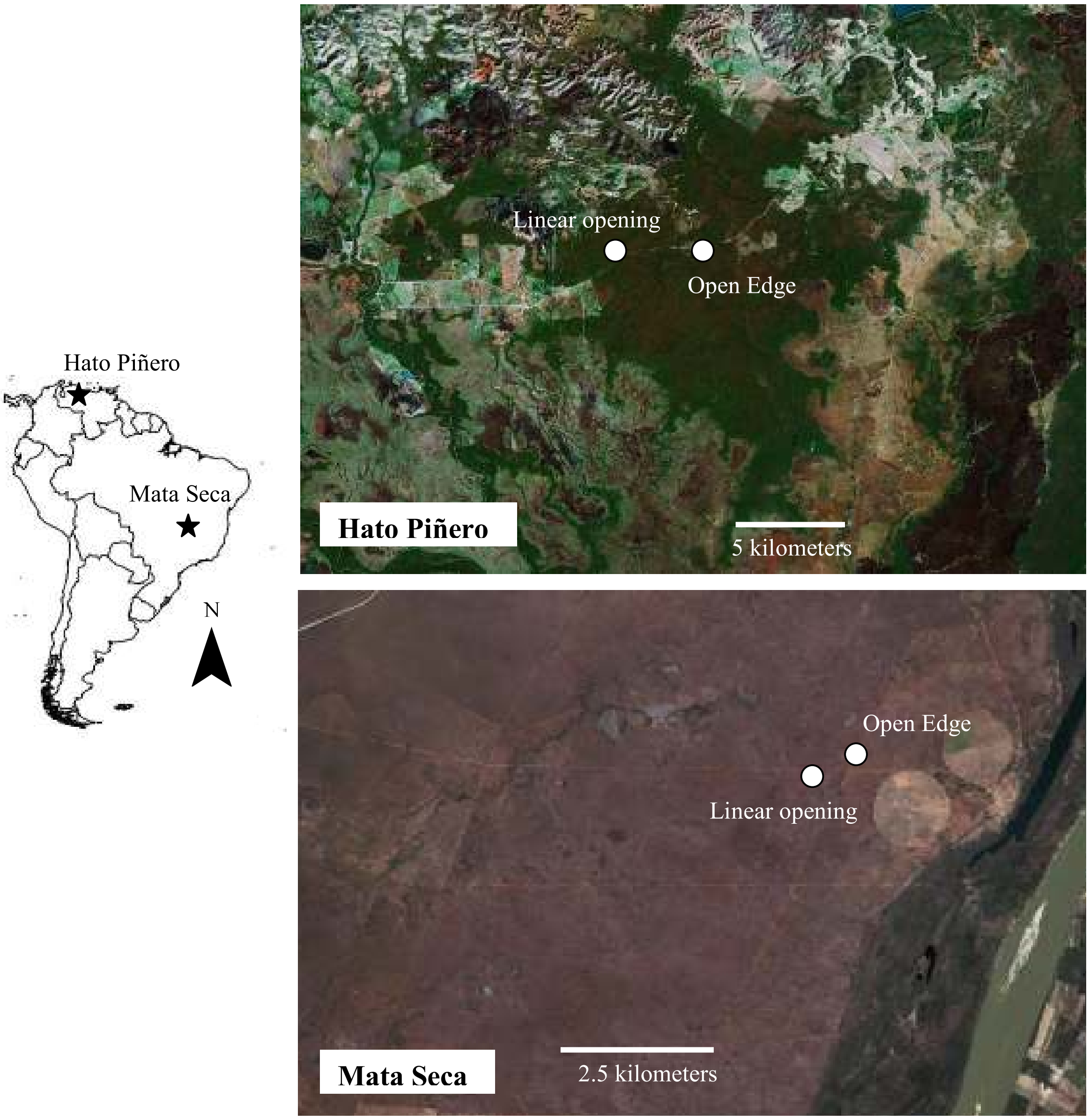
FIGURE 6-5. Relationship between Fraction of Intercepted Photosynthetically Active Radiation (FiPAR) and spectral vegetation indices (NDVI and SR). Results from linear regressions are shown for each site. Data breaks on the X axis were necessary given the difference in range of values for each site.

FIGURE 6-6. Patterns of spectral vegetation indices shown as a function of the distance from the forest edge. Values represent the mean of three adjacent pixels at the same distance.

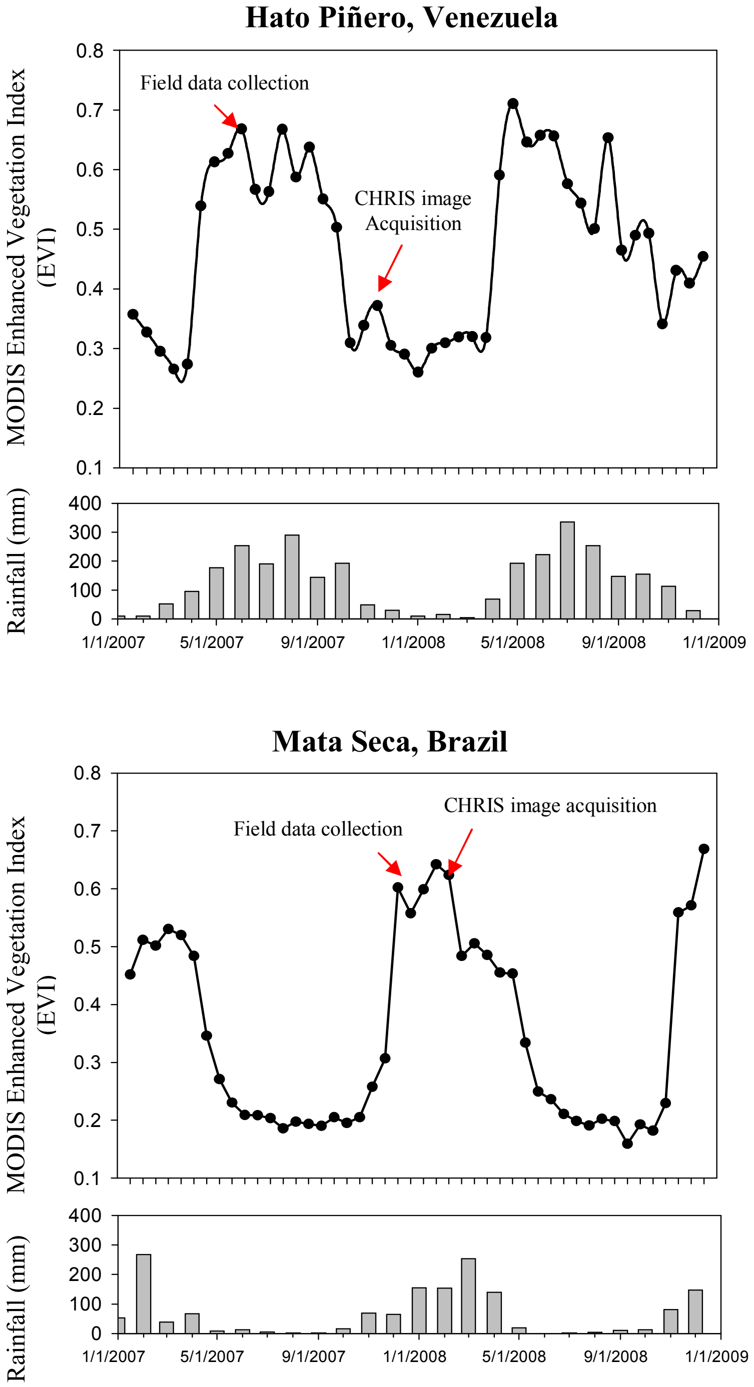
FIGURE 6-7. Comparison of the patterns of Normalized Difference vegetation index (NDVI) and Fraction of Intercepted Photosynthetically Active Radiation (FiPAR) shown as a function of the distance from the forest edge for each transect studied: (A) MS linear opening, (B) MS open edge, (C) HP linear opening, (D) HP open edge. Values represent the mean of 3 x 3 pixels window. The Y axis scales are modified for each individual transect plot in order to maximize contrast between variables.

FIGURE 6-8. Relationships between Fraction of Intercepted Photosynthetically Active Radiation (FiPAR) and Normalized Difference vegetation index (NDVI) at three different angles of observation (-36, 0 and +36). Cloud free CHRIS/Proba multiangular data with complete coverage of the transects was available for the Hato Piñero site (HP)

(Figure 6-1)


Hato Piñero
Mata Seca
N
Linear opening
Open Edge
Hato Piñero
5 kilometers
Open Edge
Linear opening
Mata Seca
2.5 kilometers

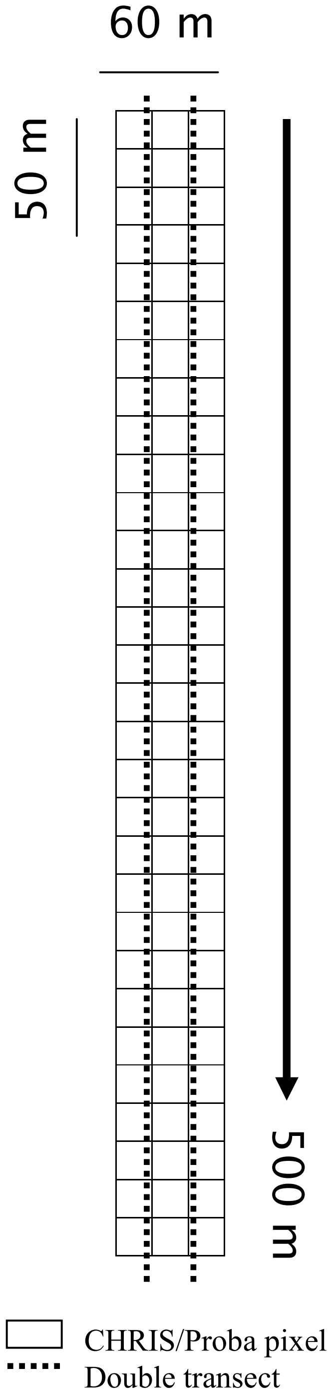
(Figure 6-2)



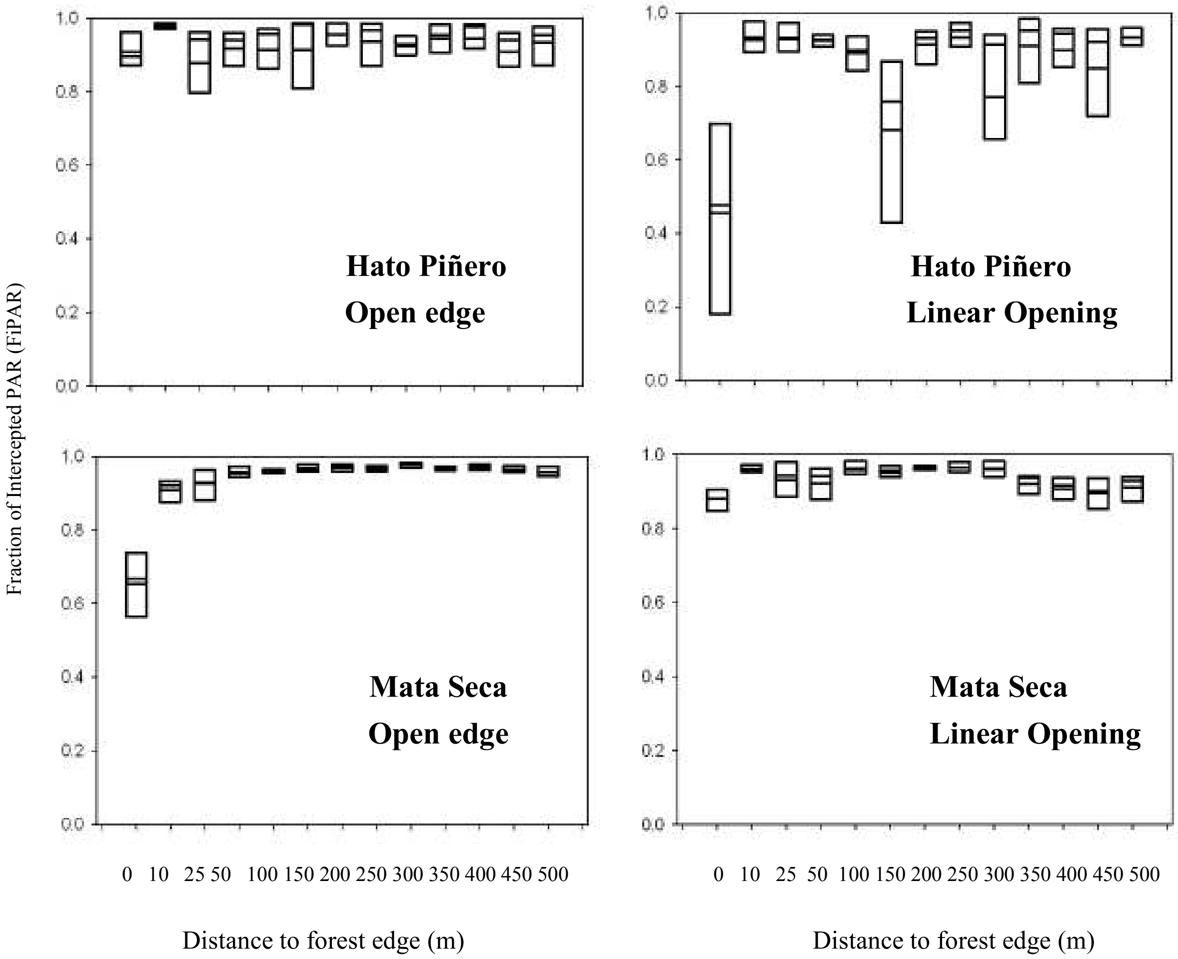
Hato Piñero, Venezuela

Mata Seca, Brazil

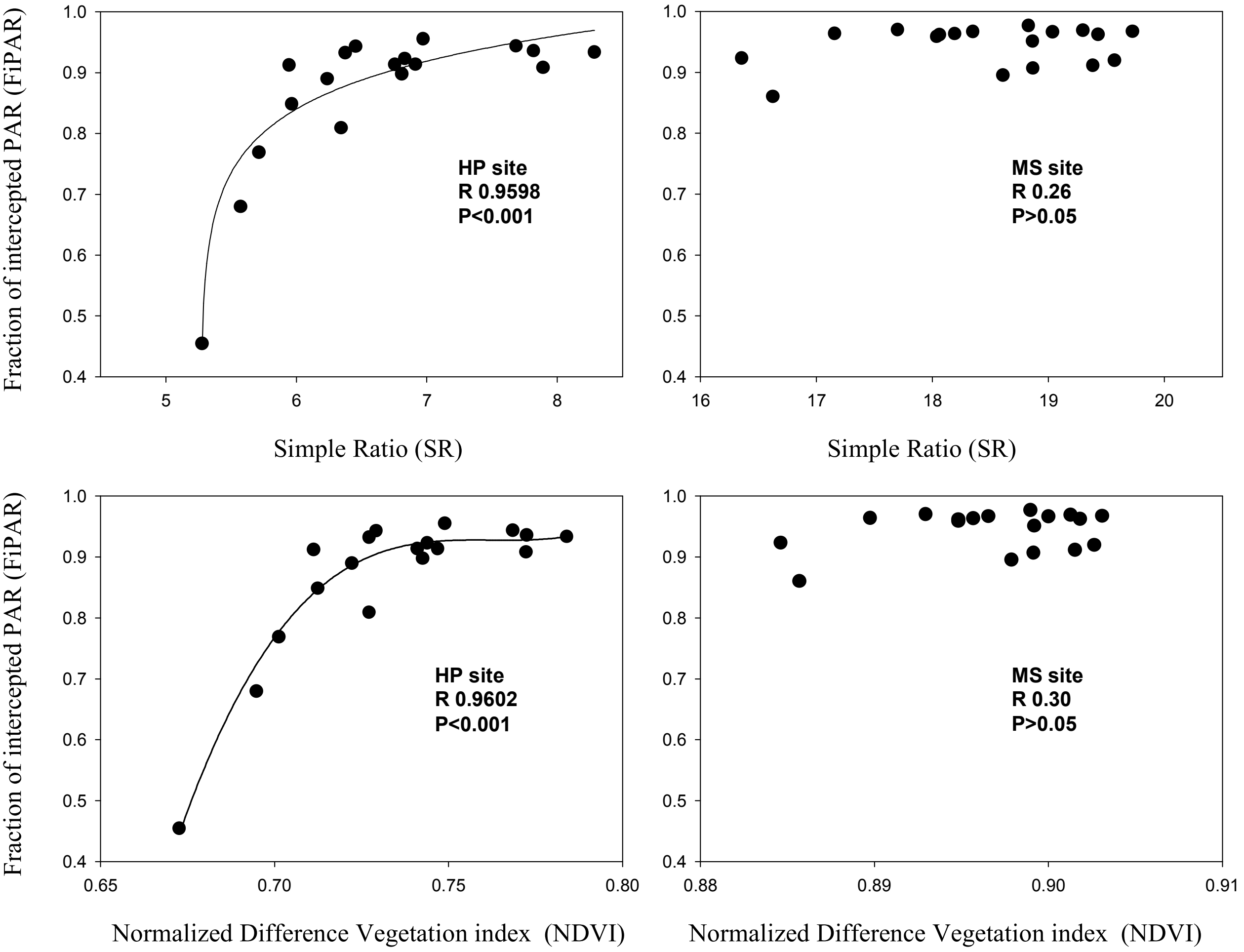
(Figure 6-3).



(Figure 6-4)

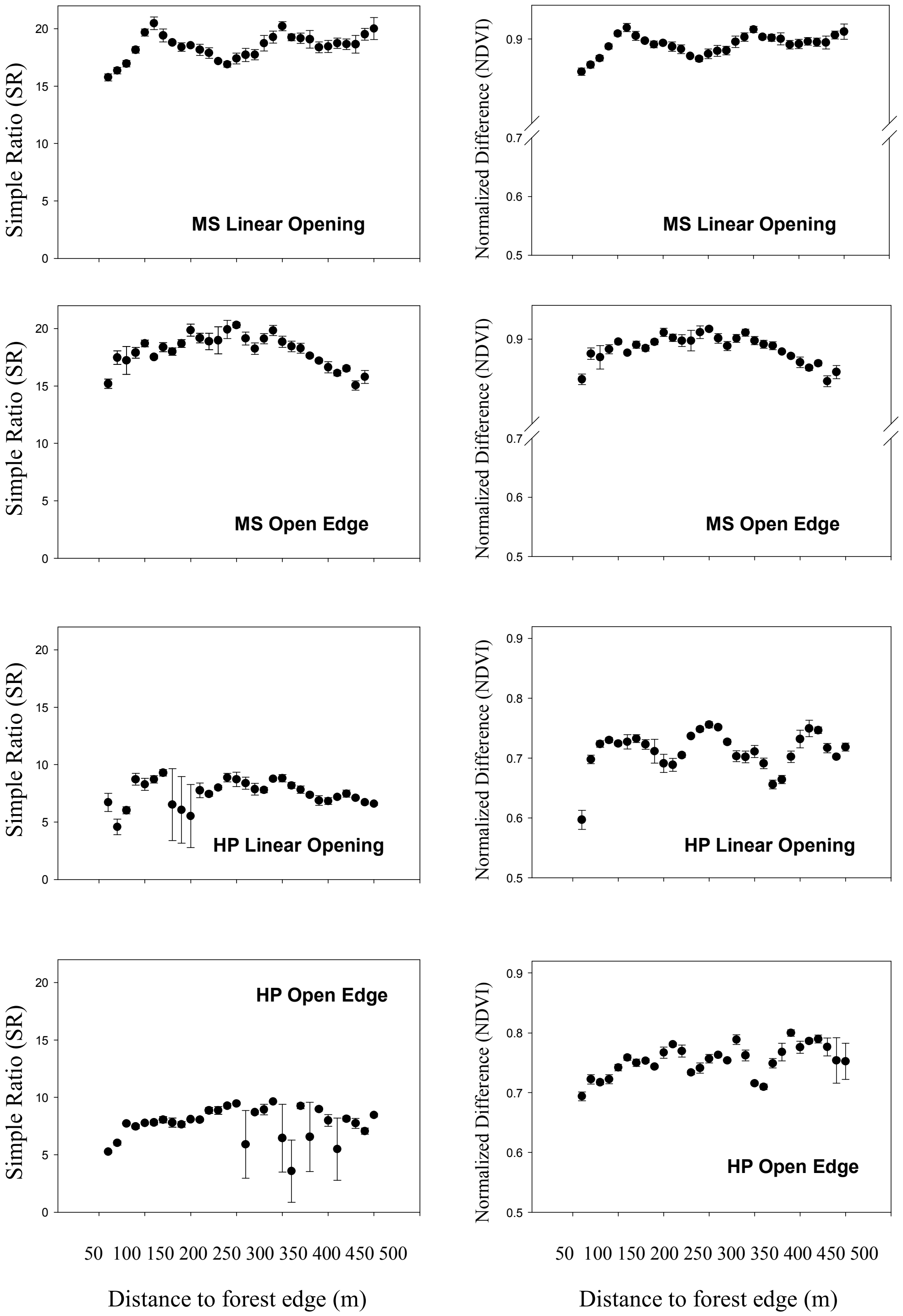

Fraction of Intercepted PAR (FiPAR)
1.0
0.8
0.6
0.4
0.2
0.0
Hato Piñero
Open edge
Hato Piñero
Linear Opening
Mata Seca
Open edge
Mata Seca
Linear Opening
0 10 25 50 100 150 200 250 300 350 400 450 500
0 10 25 50 100 150 200 250 300 350 400 450 500
Distance to forest edge (m)
Distance to forest edge (m)

(Figure 6-5)

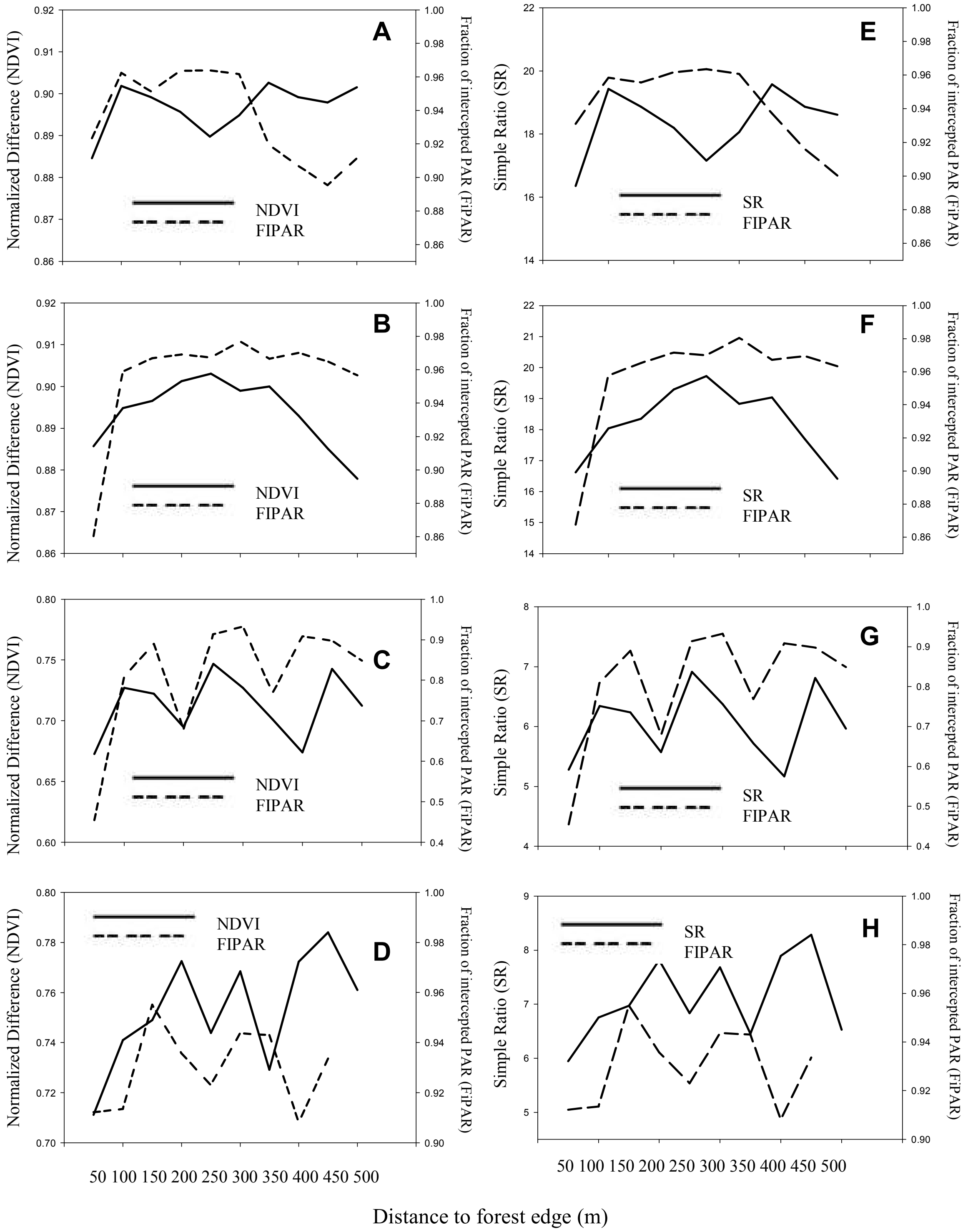


Fraction of intercepted PAR (FiPAR)
1.0
0.9
0.8
0.7
0.6
0.5
0.4
5
6
7
8
Simple Ratio (SR)
HP site
R 0.9598
P<0.001
16
17
18
19
20
Simple Ratio (SR)
MS site
R 0.26
P>0.05
Fraction of intercepted PAR (FiPAR)
0.65
0.70
0.75
0.80
Normalized Difference Vegetation index (NDVI)
HP site
R 0.9602
P<0.001
0.88
0.89
0.90
0.91
Normalized Difference Vegetation index (NDVI)
MS site
R 0.30
P>0.05

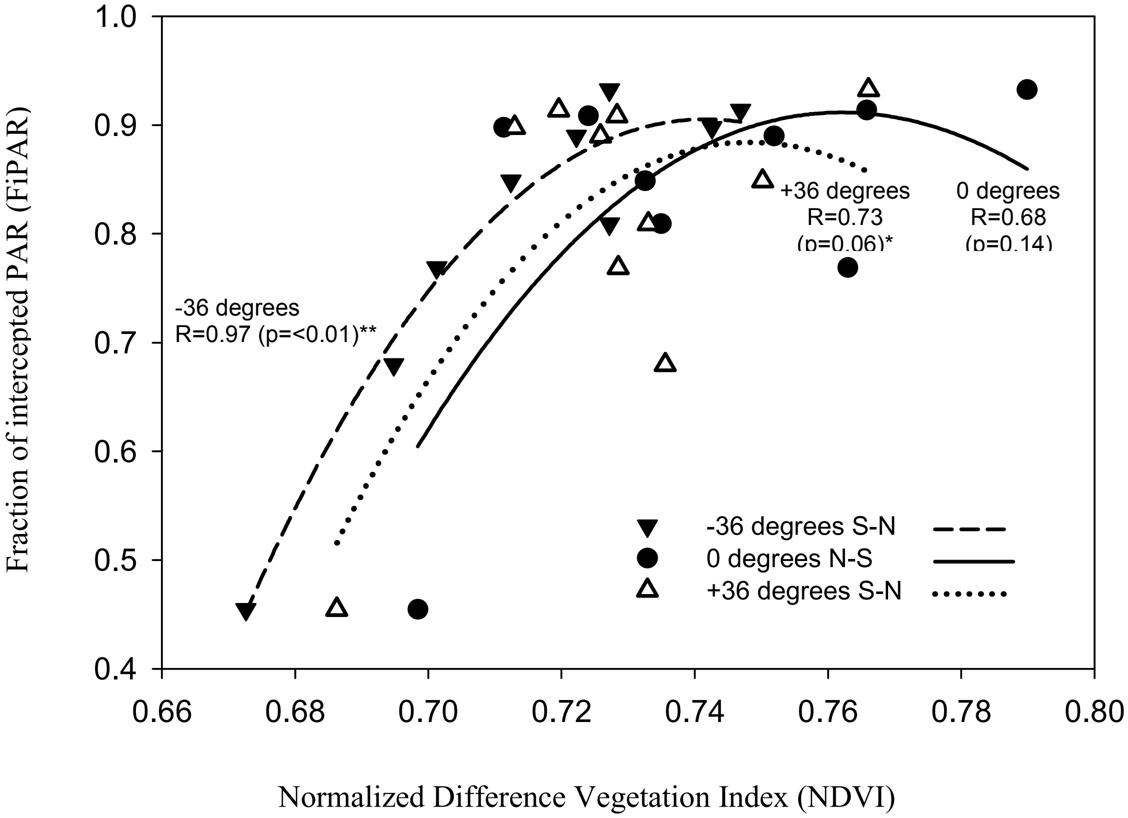
(Figure 6-6)


Simple Ratio (SR)
Normalized Difference (NDVI)
MS Linear Opening
MS Linear Opening
MS Open Edge
MS Open Edge
HP Linear Opening
HP Linear Opening
HP Open Edge
HP Open Edge
0
5
10
15
20
0.5
0.6
0.7
0.8
0.9
50 100 150 200 250 300 350 400 450 500
Distance to forest edge (m)
50 100 150 200 250 300 350 400 450 500
Distance to forest edge (m)

(Figure 6-7)


A
B
C
D
E
F
G
H
Normalized Difference (NDVI)
Simple Ratio (SR)
Fraction of intercepted PAR (FiPAR)
NDVI
SR
FIPAR
0.92
0.91
0.90
0.89
0.88
0.87
0.86
0.80
0.75
0.70
0.65
0.60
0.78
0.76
0.74
0.72
1.00
0.98
0.96
0.94
0.92
0.90
0.88
0.86
1.0
0.9
0.8
0.7
0.6
0.5
0.4
22
21
20
19
18
17
16
15
14
9
8
7
6
5
4
50 100 150 200 250 300 350 400 450 500
Distance to forest edge (m)

(Figure 6-8)


Fraction of intercepted PAR (FiPAR)
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.66
0.68
0.70
0.72
0.74
0.76
0.78
0.80
Normalized Difference Vegetation Index (NDVI)
-36 degrees
R=0.97 (p=<0.01)**
+36 degrees
R=0.73
(p=0.06)*
0 degrees
R=0.68
(p=0.14)
▼ -36 degrees S-N
● 0 degrees N-S
△ +36 degrees S-N

LITERATURE CITED

Alonso, L. and Moreno, J., 2005. Advances and limitations in a parametric geometric correction of CHRIS/PROBA data. Proceedings of the 3rd CHRIS/ Proba Workshop, ESA/ESRIN, Frascati, Italy. ESA SP-593. http://earth.esa.int/workshops/chris_proba_05/papers/06_alonso.pdf

Alves, R. 2008. Zonamento ambiental e os desafios da implementação do Parque Estadual Mata Seca, Municipio de Manga, Norte de Minas Gerais. Instituto de geociencias da Universidade Federal de Minas Gerais. Belo Horizonte, Brasil.

Asner, G.P. and A.S. Warner . 2003. Canopy shadow in IKONOS satellite observations of tropical forests and savannas. Remote Sensing of Environment 87(4):521-533.

Asner, G.P.; R. Martin . 2009. Airborne spectranomics: mapping canopy chemical and taxonomic diversity in tropical forests. Frontiers in Ecology and the Environment. 7(5): 269-276.

Asquith, N.; Mejia-Chang, M. 2005. Mammals, edge effects and the loss of tropical forest diversity. Ecology, 86(2):379-390

Bailey, S.A., M.C. Horner-Devine, G.A. Luck, L.A. Moore, K.M. Carney, S. Anderson, C. Betrus, and E. Fleishman. 2004. Primary productivity and species richness: Relationships among functional guilds, residency groups and vagility classes at multiple spatial scales. Ecography 27:207-217.

Barnsley, M.J.; J. Settle, M. Cutter, D. Lobb and F. Teston. 2004. The PROBA_CHRIS mission: A low-cost smallsat for hyperspectral, multi-angle, observations of the Earth surface and atmosphere. IEEE Trans. Geosci. Remote Sens. 42, 1512–1520.

Barducci, A., Guzzi, D., Marcoionni, P and Pippi, I.(2009) Investigating the angular and spectral properties of natural targets using CHRIS-Proba images of San Rossore test site. International Journal of Remote Sensing, 30 (3): 533-553.

Bertsch C., G. Barreto. 2008. Diet of the Yellow-knobbed curassow in the central Venezuelan Llanos. The Wilson Journal of Ornithology 120(4):767-777.

Carlson, K.C., G.P. Asner, R.F. Hughes, R. Ostertag, and R.E. Martin. 2007. Hyperspectral remote sensing of canopy biodiversity in Hawaiian lowland rainforests. Ecosystems 10(4): 536-549.

Chong, D.L.S., E. Mougin, and J.P. Gastelluetchegorry. 1993. Relating the Global Vegetation Index to Net Primary Productivity and Actual Evapotranspiration over Africa. International Journal of Remote Sensing. 14(8): 1517-1546.

Cutter, M., Lobb, D., Cockshott, R. (2000) Compact High Resolution Imaging Spectrometer (CHRIS). Acta Astronautica 46 (2-6): 263-268.

Feeley, K.J., T.W. Gillespie; J.W. Terborgh. 2005. The utility of spectral indices from Landsat ETM+ for measuring the structure and composition of tropical dry forests. Biotropica 37(4): 508-519.

Gamon J.; K. Kitajima; S. Mulkey; L. Serrano; J. Wright. 2005. Diverse Optical and Photosynthetic properties in a Neotropical Dry Forest during the dry season: Implication for Remote estimation of photosynthesis. Biotropica 37(4):547-560.

Gelhausen S.; M.W. Schwartz, C.K. Augspurger. 2000. Vegetation and microclimatic edge effects in two mixed mesophytic forest fragments. Plant Ecology 147:21-35.

Gillespie, T.W. 2005. Predicting woody-plant species richness in tropical dry forests: A case study from south Florida, USA. Ecological Applications 15(1): 27-37.

Gillespie, T.W., G.M. Foody, D. Rocchini, A.P. Giorgi; S. Saatchi. 2008. Measuring and modelling biodiversity from space. Progress in Physical Geography 32(2):203-221.

Guanter, L., L. Alonso; J. Moreno. 2005. A method for the surface reflectance retrieval from PROBA/CHRIS data over land: application to ESA SPARC campaigns. IEEE Trans. Geosci. Remote Sensing 43, 2908–2917.

Harper, K., S.E. MacDonald, P.J. Burton, J. Chen, K. Brosofske, S. Saunders, E. Euskirchen, D. Roberts, M. Jaiteh, P. Essen. 2005. Edge Influence on Forest Structure and Composition in Fragmented Landscape. Conservation Biology, Vol. 19 (3): 768-782

Jensen, J. 2007. Remote Sensing of Environment: an earth resource perspective. 2nd Edition. Prentice Hall Series in Geographic Information Science. Pearson Prentice Hall, USA.

Kalacska, M., Sanchez-Azofeifa, G.A., Calvo-Alvarado, J.C., Rivard, B., Quesada, M. 2005. Effects of Season and Successional Stage on Leaf Area Index and Spectral Vegetation Indices in Three Mesoamerican Tropical Dry Forests. Biotropica 37 (4): 486-496

Kalacska, M., Bohlman, S. Sanchez-Azofeifa, G.A, castro-Esau, K.; T. Caelli. 2007. Hyperspectral discrimination of tropical dry forest lianas and trees: Comparative data reduction approaches at the leaf and canopy levels. Remote Sensing of Environment 109:406-415

Kerr, J.T.; M. Ostrovsky. 2003. From space to species: ecological applications for remote sensing. Trends in Ecology & Evolution 18(6): p. 299-305.

Kapos, V., Wandelli, E., Camargo, Ganade, G. 1997. Edge-related changes in Environment and Plant responses due to forest fragmentation in Central Amazonia. Pages: 33-44, in Laurance, W. and Bierregaard, R. eds. 1997. Tropical Forest remnants: ecology , management and Conservation of Fragmented communities. The University of Chicago Press, USA. P. 612.

Laurance W.; Ferreira, L.; Rankin-de-Merona and Laurance, S. 1998. Rain forest fragmentation and the dynamics of Amazonian tree communities. Ecology 79(6):2032-2040.

Laurance W., T.E. Lovejoy, H.L. Vasconcelos, E.M. Bruna, R. K. Didham, P.C. Stouffer, C. Gascon, R.O. Bierregaard, S. G. Laurance, E. Sampaio. 2002. Ecosystem decay of Amazonian forest fragments: a 22-year investigation. Conserv. Biol. 16: 605–618

Laurance, W.; T. Curran. 2008. Impacts of wind disturbance on fragmented tropical forests: A review and synthesis. Austral Ecology 33: 399-408.

Liang, S. (2004) Quantitative remote sensing of land surfaces. John Wiley & Sons Inc., Hoboken, New Jersey, USA.

Malcolm, J.R. 1994. Edge effects in Central Amazonian Forest fragments. Ecology 75 (8): 2438-2445.

Oindo, B.O. and A.K. Skidmore. 2002. Interannual variability of NDVI and species richness in Kenya. International Journal of Remote Sensing 23(2): p. 285-298.

Olofsson P., L. Eklundh, F. Lagergren, P. Jonsson, A. Lindroth. 2007. Estimating net primary production for Scandinavian forests using data from Terra/MODIS. Advances in Space research 39:125-130

Phillips, L.B.; Hansen A.J.; Flather C. H. 2008. Evaluating the species energy relationship with the newest measures of ecosystem energy: NDVI versus MODIS primary production. Remote Sensing of Environment 12 (9):3538-3549.

Pohlman, C.L., S.M. Turton, M. Goosem. 2007. Edge effects of Linear Canopy Openings on Tropical Rain Forest Understory Microclimate. Biotropica 39 (1): 62-71.

Rodríguez, J. P., J. K. Balch, K. M. Rodríguez-Clark. 2007. Assessing extinction risk in the absence of species-level data: quantitative criteria for terrestrial ecosytems. Biodiversity and Conservation 16 :183–209

Serbin S., S. Gower; D. Ahl. 2009. Canopy Dynamics and phenology of a boreal spruce wildfire chronosequence. Agricultural and Forest Meteorology 149: 187-204.

Shaker, A., Nichol, J. and Wong, M. (2008) Potential Accuracy of Image Orientation of small satellites: a case study of CHRIS-Proba data. The Photogrammetric Record 23(123):275-289.

Skole, D.; C. Tucker. 1993. Tropical deforestation and Habitat Fragmentation in the Amazon: satellite Data from 1978 to 1988. Science 260 (5116):1905-1910.

Townsend, A.R., G.P. Asner; C.C. Cleveland. 2008. The biogeochemical heterogeneity of tropical forests. Trends in Ecology & Evolution 23(8):424-431.

Turner W., S. Spector, N. Gardiner, M. Fladeland, E. Sterling; M. Steininger. Remote sensing for biodiversity science and conservation. 2003. Trends in Ecology & Evolution 18(6): 306-314.

Verrelst, J. Schaepman, M., Koetz, B. and Kneubuhler, M. (2008) Angular sensitivity analysis of vegetation indices derived from CHRIS-Proba data. Remote Sensing of Environment 112:2341-2353.

Zheng, D.; Chen, J. 2000. Edge effects in fragmented landscapes: a generic model for delineating area of edge influences. Ecological Modelling 132: 175-190

CHAPTER 7 – Conclusions

The need to understand current patterns and trends on environmental change is increasingly dependent on scientific and technological advances, especially spaceborn and airborne optical remote sensing (Kerr & Ostrovsky, 2003, Balmford et al. 2002). There has been a dramatic increase in earth observation satellites and sensors over the last four decades that have been used to measure and model biodiversity and environmental change from space (Gillespie et al. 2008; Turner et al. 2003). As tropical deforestation is considered a major environmental problem, many studies using coarse and high resolution optical remotely sensed data have aimed to measure the extent and magnitude of the phenomenon and model the drivers of change (Mayaux et al. 2005 Gillespie et al. 2008; Hoekstra et al. 2005; Achard et al. 2002). Remote sensing Applications range from identifying the geographical distribution and extent of tropical forests (Eva et al. 2004, Portillo & Sanchez, 2010), measuring productivity and species composition to mapping ecosystem structure and phenology (Eva et al. 2004, Turner et al. 2003, Kerr & Ostrovsky, 2003). However, satellite remote sensing data is subject to large errors that, if unaddressed, substantially reduce their utility for ecological applications (Kerr & Ostrovsky, 2003).

In order to empower decision makers in tropical forest conservation, there is a need to integrate ecosystem-mapping methodologies with ecological theory and evaluate the utility of new remote sensing products for predicting change. The work comprised in this doctoral dissertation addresses issues that are critical to the advancement of tropical forest monitoring. The first chapter integrates the concept and techniques of optical remote sensing into the concept of biodiversity. Chapters two to five, focus on addressing knowledge gaps for quantifying and predicting changes in tropical dry forest ecological integrity and functionality. These studies contribute to the current scientific theory on the use and application of optical remote sensing tools, not only applicable in tropical dry forests, but for tropical forest conservation at the continental, regional and local level.

CONTRIBUTIONS AND IMPLICATIONS FOR FUTURE RESEARCH

Chapter Two: *Integrating Remote Sensing and Biodiversity research*

Understanding spatial patterns of biodiversity has been the long-standing interest of ecologists and biogeographers. Several factors have been able to explain the current patterns of biodiversity including time since species colonization, spatial heterogeneity, interspecific interactions, environmental stability, intermediate levels of disturbance, energy and resource availability, among others. Traditionally, ecologists have estimated biodiversity by measuring species richness, species abundance, and species evenness. This chapter summarizes how remote sensing has introduced some innovative and promising techniques to measure ecosystem extent, function, structural properties and even direct measures of species diversity. Nonetheless, the literature review clearly shows that, for ecologists and remote sensing scientists, understanding the linkage between spectral information and biodiversity is an essential and still challenging task that depends on our ability to find the proper "surrogate" ecological measurement of biodiversity that is also detectable from airborne or spaceborne sensors. Consequently, the chapter stresses out the necessity of integrated and interdisciplinary assessments using multiple spatial and spectral resolution sensors over a wide array of ecosystems in order to find relevant measures of ecosystem structural or biogeochemical properties that would be sensitive to species richness, compatible to field traditional measurements, and detectable from remote sensing. Through this chapter, I expect to contribute to this urgently needed integration of concepts and techniques and help moving the remote sensing discipline forward into complementary goals in biodiversity science and conservation.

Chapter Three: *Extent and Conservation of tropical dry forests in the Americas*

Most scientific efforts for the study and conservation of forests in the Americas have been focused on rain forests, and little attention has been paid to seasonally dry tropical forests despite its high degrees of endemism and species diversity. This chapter shows the results of an assessment on the current extent of Neotropical dry forests based on a supervised classification (Machine Learning/Decision Trees) of Moderate Resolution Imaging Spectroradiometer (MODIS) surface reflectance imagery at 500-m resolution. The analysis focused within the potential boundaries for the distribution of tropical dry forests defined by previous authors for North & Central America, the Caribbean islands and South America and accounted for latitudinal shifts in leaf phenology for imagery selection. The land cover map of Neotropical dry forests, produced with an 82% overall accuracy, represents a significant improvement on previous assessments and provides the most complete and scientifically sound source of information on tropical dry forest extent and geographical distribution existing in the scientific literature to this date.

Results showed that the total current extent of tropical dry forest in the Americas is 519,597 Km^2. We also found that 66% of the ecosystem has been already converted to other land uses while only 4.5 % is under protected areas. Mexico contains 38% of the Neotropical dry forests extent covering a higher diversity in dry forests ecoregions, however, it also has one of the lowest degrees of dry forest protection. Brasil and Bolivia contain the largest proportion of tropical dry forests under protection and the largest extent in continuous forest fragments. Low extent and high fragmentation of dry forests in countries like Guatemala, Nicaragua, Ecuador, Costa Rica and Peru means that these forests have a higher risk of human disturbance and deforestation if proper management and conservation actions are not taken. We emphasize the importance of the conservation of Neotropical dry forests given that this ecosystem not only holds high levels of biodiversity but is also an essential component of human development for rural and urban communities in developing countries of Latin America.

The use of dry season MODIS daily and 8-day surface reflectance data, the recognition and incorporation of phenological differences in forest phenology during imagery selection and the use of artificial intelligence mapping techniques are innovations introduced by this work to tropical dry forest monitoring. In order to improve the current assessment, future research should focus on assessing the spectral separability of dry forest successional stages and evergreen variants using MODIS 500-m or 250-m

Visible and Near Infrared bands, in order to incorporate these spectral signatures into the machine learning classification scheme. The resultant map could identify important forest restoration areas and seasonal refugees (evergreen islands) at a continental scale.

Chapter Four: *MODIS Active fires and deforestation in tropical dry forest landscapes*

The detection of vegetation fires using remote sensing has been proved useful for highlighting and monitoring areas undergoing rapid forest cover change. This relationship has been tested primarily for humid forest ecosystems. Using 3 x 3 sampling grids, we explored the correlation between the number of MODIS Active Fires and forest cover change in four tropical dry forest landscapes in Latin America. At the Santa Cruz site (Bolivia), correlations between the number of active fires and deforestation events were strong and significant while at Chamela Site (Mexico) and the Mata Seca site (Brazil) correlations were moderate but significant as well. In the Machango site (Venezuela), active fires were scattered and occurred in low numbers showing no correlation to deforestation events.

In general, our findings show that fires detected by the MODIS sensor may be used as predictors of deforestation in tropical dry forest ecosystems. However, in order to find ‘hotspots’ of deforestation in a tropical dry forest landscape through the use of satellite-derived fires, visualizing clusters of fires is not enough and might lead to misinterpretations. Our analysis showed that the robustness of this relationship is highly dependant on the proportion of forest cover on a given sampling box and the fire-use intensity of the land uses at each particular site. Since MODIS active fires are being widely used by local governments and environmental institutions as indicators of land use change, this finding represents an important advancement towards the validation of MODIS active fires as deforestation predictors. Future assessments should involve a large time–series dataset, such as the one used by Achard et al. (2002) and Eva et al. (2002), and should incorporate extensive information on land-use history and current patterns, in order to better understand the relationship between MODIS fires and deforestation in dry forests landscapes.

Chapter Five: *Edge influence on canopy openness and understory microclimate in two Neotropical dry forest fragments*

The specific objective of this study was to evaluate the magnitude and distance of edge influence on the amount of visible light penetrating the canopy and the magnitude and distance of edge influence on understory microclimate conditions. This study incorporates a methodology that allows direct comparison between field data and space-borne optical remotely sensed data. Typical sampling design for edge effects in tropical forests evaluate trends in single transects. In this assessment, two parallel transects were surveyed from the edge and into the forest interior (area surveyed was 60 m x 500 m for a total of 0,03 km^2). This was intended to allow capturing spatial variability and facilitating its comparison to spectral values derived from high-resolution satellite imagery such as CHRIS/Proba (see Chapter 6). Also, this study introduces the sampling of the Fraction of Intercepted Photosynthetically Active Radiation (FiPAR) as a technique to be used for evaluating edge effects. FiPAR has been used to capture forest canopy light absorption dynamics and canopy structure with significant correlations to spectral indices derived from optical remote sensing.

In this chapter, we first evaluate the structural and ecological impacts of edge influence on tropical dry forests and compare our results to similar studies in other tropical forest sites. The results in gap fraction and FiPAR show that edge influence at these sites extends to at least 300-m into these dry forest fragments although edge effects in older edges (> 25 y since creation), according to Harper et al. (2005), should be considered attenuated and affecting less than 50-100 m into the forest. Dry forest edges studied in this work, are structurally similar to young or newly created humid forest edges where both magnitude and distance of edge influence remains strong, despite the edge has been sealed by secondary growth. A tropical dry forest have lower basal area and stature than a humid forest (Pennington et al. 2006) which can make it structurally more vulnerable to lateral light penetration, striking lateral winds and gap formation following edge creation. Severe drought conditions and seasonality might be also an important factor perpetuating the strong edge influence. We suggest that further research regarding the response of plant and animal species composition and biological dynamics (both in wet and dry seasons) to edge creation in tropical dry forest fragments is needed in order to better understand the resilience and regeneration capacity of tropical dry forest to fragmentation.

Chapter Six: *Remote sensing of edge effects in dry forest fragments using CHRIS/Proba Imagery*

Extrapolating or directly quantifying the amount of forest affected by edge effects in a fragmented landscape is important in order to understand the degree of disturbance of a particular ecosystem, and the spatial distribution of its ecological processes and species abundance. However, the potential of spectral vegetation indices to detect canopy structure changes at the forest edge has not been assessed. We sampled variations in the FiPAR in four 500-m transects from the edge to the interior of dry forests in Venezuela (HP) and Brazil (MS). FiPAR values were compared to spectral vegetation indices (SVIs) - NDVI and SR - derived from CHRIS/Proba imagery (collected at a -36 degree angle of observation). The Simple Ratio and NDVI values at a -36° viewangle were significantly correlated to FiPAR values collected in the field ($P<0.05$). Variation in SVIs values along the edge showed sensitivity to changes in canopy closure and structure, especially within 150 m where decreasing values towards the edge was found in all transects. In both sites, correlation between FiPAR and SVIs as a function of distance was more pronounced when using 3x3 pixel window averaging at different distances from the edge. Mid-distance and interior variations caused by tree fall gaps were also captured by SVI values. The evaluation of the relationship between FiPAR and NDVI values collected at three different angles of observation for the HP linear opening transect, indicate that off-nadir spectral data might be critical for identifying trends in canopy cover across forest edges.

The results show that SVI values can be used as a direct indicator of changes in canopy structure and photosynthetic light absoption or as inputs to more complex models that include various parameters. However, results also show that, in order to detect edge effects from remote sensing in tropical dry forest fragments, three main aspects need to be taken into consideration: forest phenology, severity of edge effects and the view angle of spectral data. These three factors appear to be critical in order to find significant correlations between SVIs and FiPAR in tropical dry forest edges. Such factors help exacerbating changes in forest canopy and understory properties related to edge effects.

Future experiments or studies can also be designed to identify compositional and biochemical changes related to edge effects in tropical forests. Increase in the frequency of treefall gaps near the edges could also be evaluated using shadow-fraction or soil-fraction products from red and near-infrared wavelengths since these have proved to be good predictors of top-of-canopy biophysical structure (Asner et al. 2003). One of the limitations to this study is the use of a single variable collected at the field as an indicator of changes at the edge. Future field collection research should be directed towards the evaluation of edge gradients on species composition and species diversity, liana abundance, leaf area index, biomass and biochemical heterogeneity. Also, future studies should evaluate the ability of several multispectral and hyperspectral sensors, at different spatial resolutions, and angles of observations, to detect forest disturbances at the edge. Such studies should also consider assessing the distribution of edge disturbances for an entire tropical forest fragment using optical remote sensing techniques, in order to evaluate the possibility of discriminating the core-area of the fragment to the area affected by edge effects.

OVERALL SIGNIFICANCE

As deforestation advances, tropical countries in America are turning to the development of GIS monitoring systems to identify deforestation fronts and evaluate the proximate causes and consequences related to human activities. Such information is used to make political decisions aimed to promote socioeconomic activities that preserve biodiversity and alleviate environmental degradation overall. However, GIS tools and techniques for tropical forest monitoring are still in the developing and validation phase and much work is still needed in order to improve the accuracy and quality of the products. This doctoral dissertation addressed four major gaps in tropical dry forest monitoring. We used contributed to the development and validation of innovative GIS and remote sensing techniques for estimating the extent and predicting change in tropical dry forests. The results of this work are not only a valuable part of the scientific knowledge on tropical dry forest extent and conservation but also, we hope that conceptual and methodological contributions of this work will certainly open new discussions within tropical forest remote sensing research.

LITERATURE CITED

Achard, F., H. D. Eva, H.-J. Stibig, P. Mayaux, J. Gallergo, T. Richards, and J.-P. Malingreau. 2002. Determination of deforestation rates of the world's humid tropical forests. Science 297 (5583):999-1002

Asner, G.P.; A.S. Warner. 2003. Canopy shadow in IKONOS satellite observations of tropical forests and savannas. Remote Sensing of Environment 87(4): p. 521-533.

Balmford, A., L. Bennun, B., Brink, D. Cooper, I.M. Côté, P. Crane, A. Dobson, N. Dudley, I. Dutton, R.E. Green, R. Gregory, J. Harrison, E.T. Kennedy, C. Kremen, N. Leader-Williams, T. Lovejoy, G. Mace, R. May, P. Mayaux, J. Phillips, K. Redford, T.H. Ricketts, J.P. Rodriguez, M. Sanjayan, P. Schei, A. van Jaarsveld, & B. A. Walther. 2005. The Convention on Biological Diversity's 2010 target. Science 307: 212-213.

Eva, H. D., & Lambin, E. F. 2000. Fires and land-cover change in the tropics: a remote sensing analysis at the landscape scale. Journal of Biogeography, 27, 765–776.

Eva, H D., A.S. Belward; E.E. De Miranda; C.M. Di Bella, V. Gond.; O. Huber, S. Jones, M. Sgrenzaroli; S. Fritz. 2004. A land cover map of South America. Global Change Biology 10 (5), 731-744.

Gillespie, T.W., G.M. Foody, D. Rocchini, A.P. Giorgi, and S. Saatchi. 2008. Measuring and modelling biodiversity from space. Progress in Physical Geography 32(2): p. 203-221.

Hoekstra, J.; Boucher, T.; Ricketts, T.; Roberts, C. 2005. Confronting a biome crisis: global disparities of habitat loss and protection. *Ecology Letters, (2005) 8: 23–29*

Kerr, J.T. and M. Ostrovsky .2003. From space to species: ecological applications for remote sensing. Trends in Ecology & Evolution, 2003. 18(6): p. 299-305.

Mayaux, P.; Holmgren, P.; Achard, F.; Eva, h. Stibig, H-J; Branthomme, A. 2005. Tropical forest cover change in the 1990's and options for future monitoring. Phil.Trans.R. Soc. B. 360:373-384.

Pennington, T; Lewis, G.; Ratter, J. .2006. Neotropical savannas and seasonnally Dry Forests: Plant diversity, Biogeography and Conservation. CRC Press, FL.USA.

Turner W., S. Spector, N. Gardiner, M. Fladeland, E. Sterling; M. Steininger. 2003. Remote sensing for biodiversity science and conservation. Trends in Ecology & Evolution 18(6): 306-314.

Ustin S, Roberts, D., gamon J., Asner, G. and Green, R. 2004. Using Imaging Spectroscopy to study ecosystem processes and properties. BioScience 54(6):523-534.