University of Alberta

Monitoring the effects of climate change in the Tropical Dry Forest
of the Chamela-Cuixmala Biosphere Reserve

by

Jorge Mauricio Yamanaka Ocampo

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ABSTRACT

Tropical dry forests are among the most exploited and less conserved of large tropical ecosystems. This study shows advanced remote sensing techniques used to determine the land cover status of the Chamela-Cuixmala Biosphere Reserve (Mexico). Within the context of the primary basins in the region, we show tropical dry forests at three successional stages, including the location of the remaining 57,000 hectares of tropical dry forest in the area at 15 meter resolution. The research included a regional satellite-based analysis of phenology, as a critical component to understand ecosystem process occurring at the landscape level and their relationship with climate change. The seasonal development of tropical dry forests experienced shifts in time over the past decade with variations in ecosystem productivity and the length of the growing seasons. This work contributes to the understanding of tropical dry forest seasonal development and addresses climate change scenarios for continuous monitoring.

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CHAPTER 1. INTRODUCTION

The development of modern societies continues to degrade Earth systems at sometimes immeasurable scales. Land use changes, agricultural activities and urban development have transformed the composition of the atmosphere at unprecedented rates, affecting water systems and climate globally (IPCC, 2007; Salinger, 2005). The quantification of climatic drivers such as CO_2 concentrations and their timing has been considered a proxy estimate of continental carbon uptake (Buermann et al., 2007). Since the past four decades, satellite information has played a crucial role to identify and measure land cover changes at larger scales, and its implications for biodiversity (Skole and Tucker, 1993). In the tropics, rain forest has caught all research attention, leaving a critical knowledge gap in tropical dry forest research (Sanchez-Azofeifa et al., 2005a). Technology found in pioneering satellites such as LANDSAT and the AVHRR has allowed scientists to characterize change processes in vegetation, providing the context for modern studies of surface dynamics (Defries and Belward, 2000; Jensen, 2007). However with technological advancements, new opportunities emerged to improve legacy coarse resolution observations. In 2000, the Moderate Resolution Image Spectroradiometer (MODIS) on board of the Terra and Aqua satellites acquired the first series of images designed to monitor vegetation dynamics. Offering an improved spectral band design and advanced algorithms to process data (Huete et al., 2002). This new technology has allowed the quantification of complex land-atmospheric processes globally (Ganguly et al., 2010; Zhang et al., 2003).

Tropical dry forests have been catalogued as one of the most threatened ecosystems in the world (Janzen, 1988; Miles et al., 2006). However, in Mexico tropical dry forest is still the preferred biome for human settlement as well as for food production experiencing large demands, causing substantial perturbations every year (Masera et al., 1997; Trejo and Dirzo, 2000). Tropical dry forests are unique ecosystems that can serve as indicators of climate change. Their response to seasonal variations can be observed in canopy structure from remote sensors (Kalacska et al., 2005). The application of innovative remote sensing techniques has allowed an accurate estimation of the extent of Tropical dry forest remaining in the Americas (Portillo-Quintero and Sanchez-Azofeifa, 2010). Still, a multidisciplinary approach in dry forest research is needed to study the relationship of climate, human activities and ecosystem functioning at the local scale

(Sanchez-Azofeifa et al., 2005b). The effects of forest fragmentation on phenology and plant reproduction have been documented with emphasis in phenological patterns from single tree species, showing that the timing of phenological events such as flowering plays a crucial role in forest regeneration (Herrerias-Diego et al., 2006). Satellite imagery can be used to estimate tropical dry forest species composition and the effects of land use and disturbances in the ecosystem (Kalacska et al., 2004). Relationships among people and ecosystem services derived from the tropical dry forest in Chamela have been studied in detail, describing the interactions between different spheres of organization, from the stakeholders perspective, long term ecosystem research and government's socioeconomic information, presenting future scenarios that follow contrasting sets of assumptions that could bring a future scenario of overexploitation of resources, massive tourism or sustainable management (Maass et al., 2005). An approach of tropical dry forest research focused on successional stages of development is necessary to understand ecological processes and the creation of significant management strategies (Quesada et al., 2009).

In terms of its spatial distribution, the largest fraction of tropical dry forest in the Americas is located in Mexico (Portillo-Quintero and Sanchez-Azofeifa, 2010). An important area of such dry forest is found along the Chamela-Cuixmala region in Mexico. The Chamela-Cuixmala region is located along the Mexican Pacific coast, in the state of Jalisco. The region is well known for its biodiversity and natural beauty. Chamela and its surrounding areas present soils with poor organic content, where surface water lasts only a few days during the dry season (Bullock, 1986). Although climatograms, litterfall patterns and species distribution have been documented for the region (Bullock, 1986; Martinez-Yrizar and Sarukhan, 1990), the need for and improved estimate of vegetation cover at the regional level has been identified (Kalacska et al., 2008; Sanchez-Azofeifa et al., 2009). Currently there is a lack of a comprehensive land cover study for the area.

This thesis aims to contribute with a comprehensive land cover assessment of the Chamela-Cuixmala region. Providing supporting evidence to the scientific community for the evaluation of the tropical dry forest status in the region and provide evidence to strengthen local polices for conservation. This research is part of a large initiative forming the baseline for tropical dry forest monitoring in the Americas. The study focuses on the effects of climate change in tropical dry forest, and proposes an approach to monitor tropical dry forest phenology using state of the art remote sensing techniques.

Thesis goals:

Within the context of the Chamela-Cuixmala region and current tropical dry forest research, this thesis aims to contribute with the following goals:

1) To complete the first comprehensive land cover assessment of the Chamela-Cuixmala region.
2) To characterize the spatial distribution of the tropical dry forest by three stages of succession: early, intermediate and late.
3) To produce the first analysis of regional phenology in Chamela-Cuixmala as a function of tropical dry forest succession.
4) To evaluate trends in key phenological parameters and the effects of climate change in tropical dry forest.

CHAPTER SYNOPSIS

Chapter two of this thesis, *Land cover assessment of the Chamela Cuixmala Region*, introduces the first comprehensive land cover assessment of the Chamela-Cuixmala region. Satellite imagery from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) was analyzed using advanced data mining algorithms. The supervised classification included hundreds of ground control points collected in the field in 2010. A new land cover map of the Chamela Cuixmala region is presented at 15 meter resolution. The improved map includes four sub-basins of the Chamela-Cuixmala region, derived from radar imagery from the Shuttle Radar Topography Mission (SRTM). Furthermore, the tropical dry forest coverage is separated by successional stages with the decision tree approach.

Chapter three, *Modeling tropical dry forest phenology*, integrates the maps from the previous chapter focusing on regional phenology as a function of forest succession. Phenology is described for Chamela-Cuixmala during the past 12 years. This chapter discusses the impact of climate change in tropical dry forest at the landscape and plot levels, shows the spatial distribution of phenology as well as the timing of key seasonality parameters. Advanced remote sensing techniques were utilized for processing multitemporal data and perform seasonal trend analysis. We show variations of the tropical dry forest seasonality and their relationship with environmental forcing. This chapter includes a comparison of satellite-derived productivity versus field productivity and two vegetation indices tested for trends on seasonal behavior.

The contents of this thesis address key knowledge gaps in tropical dry forest status and phenology. This research is focused on the distribution of tropical dry forest and stages of succession in the Chamela-Cuixmala region, the evaluation of tropical dry forest response to climate forcing and the geographic distribution of phenology.

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CHAPTER 2. LAND COVER ASSESSMENT OF THE CHAMELA-CUIXMALA BIOSPHERE RESERVE

INTRODUCTION

The Chamela-Cuixmala Biosphere Reserve, located in the Pacific coast of Mexico is a renowned centre for Tropical dry forest research in Latin America. Since the past forty years, it has generated hundreds of articles in biological sciences and human geography (Aguilar and Noguera, 2002) providing critical information to better understand and manage one of the most endangered ecosystems in the world (Gillespie et al., 2000; Janzen, 1988). Despite this wealth of knowledge, the Chamela-Cuixmala region still lacks a comprehensive land cover characterization, limiting the research scope of many studies to relative small areas within the reserve boundaries. Larger scale ecological assessment for Chamela-Cuixmala would benefit current dry forest initiatives, facilitating monitoring efforts within the region. For instance, pioneering work by Sanchez-Azofeifa et al. (2009) described the influence of land use units named Ejidos as an indicator of the conservation status of surrounding areas.

The intent of this research is to approach the identified knowledge gap using state of the art remote sensing techniques combined with multiplatform data. The creation of a land cover map will not only benefit researchers with the identification of natural phenomena occurring around study sites, it will also be applied to modeling of the distribution of biodiversity, support land use practices and monitoring the effects of climate change in the region. This thesis aims to support trends analysis, monitor deforestation, ecosystem threats; and study the effects of extreme seasonality observations over the Tropical Dry Forest in Chamela; combining multi temporal data, to generate a scientific data set that will be further compared with Tropical Dry Forest from other regions in America.

Integrating accurate information of the extent and status of the Tropical Dry Forest at moderate spatial resolution, with biological and socio-economic data will contribute with the establishment of a solid management strategy for the payment of ecosystem services defined by Kalacska et al. (2008). Numerous research efforts have demonstrated the need for thematic maps depicting the current extent and status of vegetation cover and its importance for agencies, organizations and government (Foody, 2002b; Gillespie et al., 2008; Xu et al., 2005).

Land cover mapping has been an integral component of remote sensing. Since the last seventy years, societies of developed countries have tried to characterize their surroundings for many economical and institutional reasons (Jensen, 2007). Such task relies on several data management procedures that range from cleaning and pre-processing the data, formatting and interpretation. All with the common intent to assist scientists, organizations and governments in performing informed decisions. Such exercise plays a pivotal role in the difficult task of managing resources, policy making and the science involving geospatial data. According to Homer et al. (2004) relevant land cover information provides a framework in which multiple geographical applications can be supported by the different levels of government and organizations.

Classification efforts are part of a wide variety of activities towards problem solving, including forecasting and decision making with currently available information (Muchoney et al., 2000). In this context, the classification of remote sensing data can be defined as a method in which certain procedures are repeated systematically over different areas (Foody, 2002a).

ADVANCEMENTS IN LAND COVER MAPPING

The techniques used in land cover mapping are dictated by the scope of the project and the scale of the available information. As an example, mapping vegetation over small regions (municipalities) has traditionally being achieved by the interpretation of field data and reconnaissance efforts at the ground level. However, it is possible to gain a more significant insight of the landscape properties by the interpretation datasets covering large areas such as remote sensing data, including aerial photography and satellite information in the visible and other regions of the electromagnetic spectrum (Jensen, 2007).

In land cover mapping theory, a classification where classes are presumed to be known can be referred to pattern recognition, supervised learning, or image discrimination (Foody, 2002a; Hwahwan and Cha, 2008). Despite the simplicity of such definition, the process of selecting land cover units depends significantly on the perception and experience of the user, data attributes (such as origin, date, quality), preprocessing and the selected techniques for the analysis making land cover definitions complex (Lucas et al., 2007).

The process of land cover mapping is commonly done by separating the landscape into areas with homogeneous distribution of vegetation, corresponding to land cover classes (Lowry et al., 2007). While excluding a problematic class (such as clouds) from an image can improve the classification results by removing noisy data, the assumption that training classes selected for an area will contain all classes actually existing, can potentially reduce the quality of the classification (Foody, 2002a). Furthermore, classifications are sub divided in supervised and unsupervised. Both techniques differ in that for unsupervised classifications, the assignment of classes is achieved through the application of a clustering algorithm (Michie et al., 1994). Unsupervised classifications are useful when a reliable source of training data is not available, and also as a first exploratory technique, to analyze class separability. They can also serve to aid supervised classifications with data clusters for training (Hwahwan and Cha, 2008). An identified limitation present in traditional classifications techniques is the assumption of normally distributed data and exclusivity of classes. In practice, this assumption may fail as in the case of moderate spatial resolution data where an image pixel can include a mixture of several classes (Foody, 2002a).

Classification studies deal with the nature of classes and their definitions in which three different scenarios are proposed: first, classes correspond to different populations. Second, classes result from predictions and third, classes are defined by their attributes. While hard classifications (where each pixel belongs to a single class) are unable to deal with heterogeneous distributions of land cover, classification tree analysis have emerged as an alternative method (Foody, 2002a). Here, partial distributions can be accounted for, while performing a core non parametric classification (also referred to as soft classification).

Decision tree analysis is defined as the classification procedure that partitions the data into subdivisions obeying a set of tests controlled by each branch until reaching all the leaves of the decision tree (Friedl and Brodley, 1997). Thus, providing a more complex technique supported by fuzzy logic that has shown clear advantages when dealing with mixed pixels (Lucas et al., 2007).

DATA MINING

The term “Data Mining” originated in 1943 as a precondition for intelligent systems in an automatic computing engine lecture by A.M. Turing (Carpenter and Doran, 1986). Data Mining was developed to deliver procedures comparable to, or better than human interpretation based classifications. It has the advantage of being robust and more comprehensive. Therefore, data mining involves automated computer tasks based on logical operations that need to be “trained” in order to “learn” a task from a series of examples, based on a decision-tree approach, where the classification originates from logical rules defined by the user (Michie et al., 1994).

During classification of remote sensing data, patterns of vegetation are treated as an integrated reflection of physical, structural and chemical factors that exist in a given area (Landenburger et al., 2008; Lowry et al., 2007). Therefore, the main purpose behind supervised classification is to provide comprehensive land cover maps to serve a wide range of purposes. The importance of global thematic maps has been well established by a vast amount of literature, with emphasis in land cover change (Defries and Belward, 2000). Examples of such efforts include a campaign performed by Lowry et al. (2007) to map land cover of the southwest United States using hundreds of satellite images, resulting in a detailed thematic map of 125 classes at 30m resolution and high accuracies. Among others, applications of supervised classification have included oil spill global maps (Brekke and Solberg, 2005), monitoring changes in deforestation and urbanization (Foody et al., 2007), urban water management (Makropoulos et al., 2003) and particularly relevant to this thesis; an estimation of the Tropical Dry Forest extent in the Neotropics (Portillo-Quintero and Sanchez-Azofeifa, 2010).

Research in computer science has led to the development of new algorithms capable of performing advanced pattern recognition, clustering analysis, and spectral band separations (Brekke and Solberg, 2005; Friedl and Brodley, 1997; Hwahwan and Cha, 2008).

In order to classify large geographic regions in the United States, Homer et al. (2007) used a commercial algorithm called See5 in combination with moderate resolution satellite imagery and digital elevation data, achieving accuracy estimates of 98 percent. See5 is a data mining application capable of handling large datasets, to find and extract patterns; combining artificial intelligence with user knowledge trough a series of training steps. The See5 algorithm has been used in land cover studies with highly accurate results ranging from 83% to 98% at diverse spatial scales, from regional applications to single tree species mapping (Kandrika and Roy, 2008; Landenburger et al., 2008; Moisen et al., 2006; Portillo-Quintero and Sanchez-Azofeifa, 2010; Su et al., 2002). Currently the National Land Cover Database mapping tool (NLCD) has been implemented in the ERDAS software environment which can perform image classifications based on the See5 decision rules and classification trees (Homer et al., 2007; Homer et al., 2004).

One of the major challenges in classification tree analysis is to relate them to a geographic location within a GIS environment (Lowry et al., 2007). The NLDC mapping tool (Homer et al., 2004) is a state of the art program that can deal with virtually unlimited number of cases by calling the See5 algorithm; it is also able to translate and apply decision rules or classification trees to any given geographic location, regardless of its size and data format. Decision tree classifiers have the advantage of being non parametric, thus they do not require the assumption of normal distribution in the training data (Lowry et al., 2007). This characteristic allows us to incorporate ancillary data that otherwise would not be accepted by traditional classification methods. They also have shown to perform equal or better than the maximum likelihood algorithm (Friedl and Brodley, 1997).

OBJECTIVES

Within the context of the current literature review and identified gaps in the field of knowledge, the main goal of this research was to complete the first comprehensive land cover assessment of the Chamela-Cuixmala region.

The results from this work will be used as a framework to evaluate the impacts of climate change on regional phenology as a function of Tropical Dry Forest successional stages. Therefore, a secondary objective is to characterize the spatial distribution of

Tropical Dry Forest by three stages of succession: early, intermediate and late at the regional level.

METHODS

The use of remote sensing for the purpose of generating knowledge about the status of the land cover has been widely approached with numerous techniques and different levels of success (Foody et al., 2007). The land cover assessment was divided in two logical steps. First we defined the extent and spatial resolution at which the mapping would have adequate levels of significance to perform not only land cover mapping, but the integration with phenological investigations as well, definition of the study area, possible sources of data, and selection of the sensor. Second, current techniques for the discrimination of land cover classes were studied. Based on the literature, the data mining approach was selected according to the characteristics of the Chamela-Cuixmala region such as the altitudinal gradient and occurrence of several types of vegetation. Moreover, we acquired an extensive library of ground control points for training the classifier. For instance, we selected the dry season as the most suitable time of the year to discriminate Topical Dry Forest from the rest of the landscape (Portillo-Quintero and Sanchez-Azofeifa, 2010) and to separate stages of succession within the Tropical Dry Forest by their spectral features (Arroyo-Mora et al., 2005).

STUDY AREA

The Chamela-Cuixmala Biosphere Reserve is located in the state of Jalisco, Mexico along the Pacific coast. Decreed in 1993 the reserve covers 13,142 Ha. The study area encompasses the total area of the reserve and extends to the four sub-basins that fully contain the reserve boundary. The study area included the sub-basins of Cuixmala with an extension of 109,298Ha, Chamela 21,649Ha, Careyes 2,238Ha and Los Cajones 1,817Ha (figure 2.1). The study area covers 1,350Km^2 with an altitudinal gradient ranging from the sea level along the coast that gradually increasing towards the northeast in to the mountain range known as Sierra Madre del Sur, where the altitude reaches 1,700MASL. The topographic conditions in the area have allowed the presence of several vegetation types, from Pine-Oak forests (mountain range), riparian vegetation, Xerophytic vegetation, coastal dunes, sub-deciduous dry forest, Tropical Dry Forest, and mangrove; converted vegetation such as pastures and agriculture fields is also present and plays an important role in the regional landscape. The dominant woody species are represented by legumes and the genus *Bursera*, representing the most diverse genus in the Pacific Coast of Mexico (Becerra, 2005). Burseras are deciduous trees with a geographic distribution limited by climatic conditions; this vegetation is well adapted to moderate to warm climate, and highly seasonal precipitation.

In the Pacific coast of Mexico, inter-annual precipitation patterns are controlled by the occurrence of tropical cyclones and the presence of El Niño Southern Oscillation (ENSO), which contributes to seasonal variations in precipitation, by decreasing precipitation during the rainy season and incrementing precipitation events at the dry season (Garcia-Olivia et al., 2002). In the Chamela-Cuixmala biosphere reserve the average annual precipitation for the period 1977-1984 was 748mm (Bullock, 1986) and 755mm for the year 2000 to 2010. The region has a climate defined as dry tropical with a winter dry season and a mean annual temperature above 22°C (Bullock, 1986).

The Chamela-Cuixmala region faces several threats due to land transformation, Illegal hunting and the lack of adequate ranching practices. These are combined with climate forced susceptibilities due to changes in global circulation patterns and warming (Stahle et al., 2009). The Chamela-Cuixmala Biosphere reserve receives its name from the rivers Chamela and Cuixmala that make their path through the reserve and discharges their waters in the Pacific Ocean.

In the region, mature Tropical Dry Forest can be found with abundant yet very intermittent stream networks (Martinez-Yrizar and Sarukhan, 1990). The raining season starts in June and lasts to mid November, with a dry period of six months. The median annual precipitation is 748mm in Chamela that peaks from August to October, and 782mm in Cuixmala. In this region, the Tropical Dry Forest has more than 10% of endemic species (INE, 1996).

According to Nassar et al. (2008) in the framework established for the Tropical Dry Forest research, successional stages of tropical dry forest were defined as early, intermediate and late (figure 2.2). The early stage represents areas recovering from recent disturbances where the vegetation is between 3 to 5 years old. These areas include pasture and agriculture fields that have been protected since the last disturbance. For instance, such areas generally contain particularly young trees and herbaceous vegetation with abundant open spaces. From the remote sensing perspective, such areas could be registered as bare soil from coarse resolution sensors (>500m spatial resolution). The intermediate stage shares similar circumstances (for example: land use history) as early Tropical Dry Forest, but the age of the forest is between 10 to 15 years. Here, a slightly higher diversity of herbaceous plants and small trees can be present but still with significant canopy openness. The late stage of Tropical Dry Forest integrates a combination of bushes and trees of mature forest 50 years and older, where the soil contains significant amounts of organic matter with distinct spectral characteristics.

FIELD CAMPAIGN

In order to generate the rules and decision trees for the classifier, a database of ground control points was collected in the field (figure 2.3). The field campaign was carried out during the period of July-August 2010. Data was collected with a hand held GPS receiver Garmin™ Map60CSx, accompanied with geo-tagged photographs per every sample location. Several horizontals and vertical transects were followed along main roads, trails and ravines, covering significant areas to include all land cover classes. Field control points were collected on the location of existing TROPI-DRY parcels (including different stages of Tropical Dry Forest) for the accuracy test. The final database included 354 training sites, and an additional 2,800 surrogate training points collected in ArcMap 10 through the interpretation of high-resolution imagery from Digital Globe.

DATA SOURCES

The use of ancillary datasets (types of data include soil maps, vegetation indices, water indices, zone buffers and elevation values) is well known to provide better class discrimination while performing supervised classifications (Hwahwan and Cha, 2008; Lucas et al., 2007). The geographic dataset for supervised classification included multiplatform satellite and space shuttle imagery (Table 2.1). The imagery was projected to the UTM WGS 84 zone 13N coordinate system and the Digital Elevation Model was re-sampled to a 15m pixel size by a cubic convolution approach in ERDAS. Special emphasis was taken on the adequate co-registration of imagery in order to minimize spatial error.

The classification included as the first input layer an Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) reflectance image (bands 1-3) of the visible and near infrared spectrum, with a spatial resolution of 15m from the year 2006. These images were previously corrected for geometric and atmospheric effects by the ASTER data team with code from the University of Arizona.

Two vegetation indices were utilized as ancillary data in order to improve class separability as shown in Arroyo-Mora et al. (2005). The Normalized Difference Vegetation Index (NDVI) obtained from the ASTER bands 2 and 3 in ERDAS as:

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$$

Where NIR is the near infrared spectral band, and Red is the visible band in the red region of electromagnetic radiation. The NDVI is sensitive to chlorophyll, therefore is a strong indicator of biomass and vegetation health (Huete et al., 2002). The second vegetation index derived from ASTER imagery was the simple ratio:

$$SR = \frac{(NIR)}{(Red)}$$

Where the NIR is the near infrared band, and Red is the red visible band, as for the NDVI, the simple ratio has been found to be highly correlated with green vegetation cover in homogeneous soils (Duncan et al., 1993). Ancillary data from the digital elevation model were obtained from the Shuttle Radar Topography Mission (SRTM) derived from Jarvis et al. (2008) including aspect and slope.

CLASSIFICATION

Recent studies have shown that, while performing an image classification, errors associated with radiometric resolution and image geometry can be reduced by the selection of the most suitable resampling algorithm (Homer et al., 2004). In this context, during the pre-processing stages of the classification and to account for artifacts in the resampling process, the digital elevation model and related products (continuous data) were processed with a cubic convolution algorithm. In the other hand, land surface reflectance in the visible and NIR (discrete data) were processed using a nearest neighbor approach, because this interpolation method is better at preserving cell values and reducing the spatial error to one half of the cell size (ESRI, 2010).

Characterizing the whole extent of the Chamela-Cuixmala region required three ASTER scenes to obtain full coverage of the study area. The first classification exercises were performed on image mosaics; yielding significant levels of confusion and low accuracy results (suspected problems related to pixel brightness and spatial distribution of classes). For instance, the south west corner of the Chamela-Cuixmala basin contains only three of the ten classes selected for area. Thus, a series of explorative tests were performed showing that individual classifications resulted in more accurate estimates than the mosaic approach. Consequently, individual sets of vegetation indices, ancillary data and training points were created for each scene. The final step consisted in the creation of a single thematic land cover map, constructed by merging individual land cover maps in to a single map.

Our regional analysis of the Chamela-Cuixmala land cover used a total of ten land cover classes as described in table 2.2. The selected land cover classes included Mangroves, located at the south of the area of study, strictly associated with estuary ecosystems near the coast of Jalisco; and represented in its majority by mangrove swamp with trees of the genus *Rhizophora*. Also, included were riparian vegetation distributed along the ravines and drainage channels of intermittent characteristics. This class represented about 10% of the study area, sharing species encountered in the Tropical Dry forest but presenting evergreen behavior, and abundance of trees of the genus *Ficus* and *Taxodioum*. This class was clearly identified by visual photo interpretation of images collected in the dry season, due to the presence of green canopies and higher NDVI values than the dry forest.

The second principal land cover group of the study was Evergreen forest (22%) located at elevations from 600 to 1,700 MASL. This class was composed mainly by species of the genera *Quercus*, *Abies* and *Pinus* the first are Oak trees and the second are

Pine trees being *Abies* a genus of trees native of Mexico (www.iucnredlist.org). The final land cover map was refined by using a 3 by 3 morphological operator in ERDAS Imagine.

VALIDATION

To avoid errors caused from class assumption, the selection of land cover classes was designed to account for all principal vegetation types existing in the region; with careful definition of "no data" pixels, and samples containing urban and manmade features (Foody, 2002b). Post processing techniques such as the use of morphological operators to remove noise, have shown improvements in the quality the thematic map, and help prevent possible misclassified pixels (Hirano et al., 2003). It is known that misleading accuracy of reports can be generated from using the same data to train and validate classifications (Michie et al., 1994). For instance, this scenario would theoretically represent a decision tree with an unlimited number of leaves, returning nearly perfect accuracy estimations.

Friedl and Brodley (1997) described a method to discard biased classifier performance evaluations, by using 70% of the data for training, 20% for pruning, and 10% for testing. Following that method, we approach our classification by allocating 70% of the points collected in the field as input for training the classifier and 30% of the field data for the accuracy assessment. The use of probability sampling has been accepted while performing accuracy estimations (Lowry et al., 2007). In some scenarios, the percentage of correctly allocated cases has been used to validate the results of quality assessments (Foody, 2002a; Muchoney et al., 2000).

For this Thesis, the implementation of probability sampling to estimate map accuracy was created in the ERDAS environment. We followed the confusion matrix approach described in Foody (2002b) having as estimate indicators the user and producers accuracy. Further, the selection of pixels containing Tropical Dry Forest only was implemented by geospatial analysis with emphasis in the dry forest class. Once the areas with Tropical Dry Forest were successfully identified, the rest of the pixels were assigned data values through spatial modeling, resulting in optimized input layers for Tropical Dry Forest mapping per stage of succession.

Although land cover maps are approximations of the state of the environment at a specific time, classification efforts must be carefully designed and implemented in order to achieve the best possible interpretation. Regarding the use of validation points for the creation of a confusion matrix, field measurements were acquired by proper calibration of the GPS unit, taking as many points as necessary to represent the classes in the study area. For remote locations with limited accessibility and constrained by the landscape, measurements from high resolution imagery were taken as a surrogate from the field data. Moreover, fuzzy classification efforts can be easily compromised due to the high cost of field data collection (Foody et al., 2007). Hence, we provide an application where the use of surrogate data was an appropriate alternative in land cover mapping efforts.

RESULTS

Tropical dry forest was found to be the most abundant land cover class of the study area (40%). It is located among the four sub basins and has a northern boundary defined by topography. This class can be found at elevations that range from a few meters above sea level (MASL) to 1000 MASL. Tropical dry forest included semideciduous Tropical Dry Forest, defined as plant communities that only lose about 75% of their leaves during the dry season (Martinez-Yrizar and Sarukhan, 1990).

The challenges associated with the correct identification of the pixels that belong to each group includes the spectral similarities between early and intermediate dry forest stages and with pasture. Since the species composition is similar with the exception of few introduced plants used by ranchers as shade for their cattle and limiting boundaries. Evergreen forest presented one of the highest NDVI values together with Mangroves and Agricultural fields, improving their separation from other classes.

Once machine-learning techniques are well established, they can go alone with little human intervention, but the process of gathering all their knowledge can take from months to years of work (Michie et al., 1994). With rapid changes in sensor development and emerging techniques in monitoring resources, the time to learn how to perform a classification has become a sudden necessity; therefore, adjustments to the method must be efficiently done.

Accuracy estimations can be obtained from the training data set, by comparing the unknown classifications to the known classifications. Further, the proportion of correct cases must be randomly distributed. It is necessary to pay attention to a common omission encountered by Foody et al. (2007) where the proper acquisition of no-interest classes was missing from the field data; their solution consisted of a binary classification to separate classes of no-interest from the rest of the data.

Results of the land cover map and Tropical dry forest stages map are summarized in tables 2.3 and 2.4, where the agreement between land cover units or classes correctly allocated is shown by using current techniques in accuracy assessment with the application of a confusion matrix. The Kappa coefficient is reported for each table; this index has been widely used to compensate for the effect of a class agreement due to chance (Foody, 2002b). The land cover map of the Chamela-Cuixmala Biosphere reserve for the year 2006 (figure 2.4) was completed, with an estimated users accuracy of 98% for the Tropical Dry Forest class, and 100% of producers accuracy, meaning that errors due to omission were minimized for that particular class. The overall accuracy of the land cover map was 92%, which represents a significant result while compared with classification techniques used in similar studies with 85% overall accuracy (Foody, 2002b).

The classes that were separated with higher levels of confidence were the expected major clusters of pixels of beach, water, evergreen forest and urban, with estimations close to 99.9% users accuracy. The class with the lowest users' accuracy (most commission errors) was seasonal agriculture (82%). This related to the composition of its signal including a mixture of vegetation types, bare soil and pastures that were not clearly separated by the decision tree. The final map of Tropical Dry Forest by successional stages (figure 2.5) has an estimated overall accuracy of 84.4%. Accuracy estimates show that the intermediate stage is one of the most difficult classes to discriminate, perhaps due to its similarities with the early stage in terms of open canopies; and similarities with the late stage at more developed intermediate stages. The late stage reported the highest producer's accuracy (97%) followed by intermediate (87%) and early (70%); here early stage presented the highest degree of omitted values.

In our first approach, while trying to separate successional stages by using the visible bands and near infrared plus vegetation indices, the results were not significant for the scope of the research. A common expected target accuracy of 85% is suggested in Foody (2002b). Furthermore, the approach that provided best results to map successional stages consisted in the addition of vegetation indices clusters to the training data and the assessment of class separability in terms of their Normalized Difference Vegetation Index and Simple Ratio thresholds as shown in (Arroyo-Mora et al., 2005).

Land cover results show an estimate of 57,000 Ha of Tropical Dry Forest remaining in 2006 along the Chamela-Cuixmala region (figure 2.6). The distribution of Tropical Dry Forest successional stages shows that 75% of the ecosystem is represented by the late stage, 21% intermediate and 4% early (figure 2.7). The largest amount of Tropical Dry Forest is located within the Cuixmala basin (Table 2.5). With close to 38,000Ha; the Tropical Dry Forest protected by the Biosphere Reserve is less than 20% of the dry forest coverage (estimated of 11,182Ha of Tropical Dry Forest inside the Cuixmala sub-basin).

This clearly indicates a need for policies to manage the ecosystem for the whole basin and promote sustainable development, since 66% of the dry forest is present in the Cuixmala basin only. The second largest distribution of Tropical Dry Forest is inside the Chamela sub-basin (nearly 16,000Ha) representing 27.7% of the Tropical Dry Forest estimated for the region.

DISCUSSION

Parting from the common goal of obtaining a thematic map representing the environment closest to reality, accuracy becomes a key factor that relates to the confidence in using the rules applied by the classifier, through the examination of the correct assigned cases or obtaining the least amount of error. Given that accuracy requirements for each class are determined by the scope of the project, the larger efforts placed over Tropical Dry Forest discrimination yielded the highest accuracy reports fort that class (99%).

Land cover results show that less than 20% of the identified Tropical Dry Forest is under regulated use and protected by the Reserve. The rest of the ecosystem faces complex processes of transformation and lacks adequate management policies, making the future uncertain for such an invaluable resource.

Based on Tropical Dry forest estimations per basin area, considerable efforts and resources should be directed at the Cuixmala basin that contains the largest amount (66%) of Tropical Dry Forest remaining in the region. Although Los Cajones and Careyes basins are smaller sub-basins, their dominant ecosystem is tropical dry forest (81% and 83% respectively) making suitable to monitor dry forest phenology from remote sensing, since the signal captured by the moderate resolution sensors would include a better representation of the tropical dry forest signal.

The tropical dry forest of the Chamela-Cuixmala region has a large proportion of mature forests (75%) compared to intermediate (21%) and early (4%). Such distribution of tropical dry forest succession needs to be closely monitored in order to assess current management practices, as well as land use practices in the region. And to determine if changes in dry forest composition are mainly human derived or induced by climate change.

CONCLUSIONS

Our findings support that land cover mapping of Tropical Dry Forest can be achieved by the data mining approach. Data mining provides advantages not found in other classification methods, allowing the definition of mapping classes otherwise nearly impossible to discriminate by other algorithms. The versatility of data mining for land cover mapping allows the use of several data types. Vegetation index clusters were a key variable that assisted the supervised classification.

Vegetation index clusters substantially improved the discrimination of successional stages regarding their “greenness” thresholds. The use of data mining accompanied by pre-processing techniques shows that decision tree classification represents a robust method for land cover mapping, with emphasis in subclass separability. For instance, Tropical Dry Forest successional stages were identified at significant levels of accuracy. This method has performed better than traditional alternatives and has shown to perform better than the maximum likelihood algorithm and linear discriminating functions (Friedl and Brodley, 1997) providing a structured framework that could be implemented other Tropical Dry Forest studies. The creation of a regional land cover map of the Chamela-Cuixmala biosphere reserve from satellite data at 15m spatial resolution will provide an essential tool for education, conservation and collaboration among the members of the Tropical Dry Forest network.

The importance of successional stages as a functional group relies in the ability to link several dry forest parameters to other human and biophysical dimensions (Quesada et al., 2009). This thesis will contribute with the role of Tropical Dry Forest in the Pacific coast of Mexico, as part of collaborative efforts to better understand and manage the Tropical Dry Forest of the Americas.

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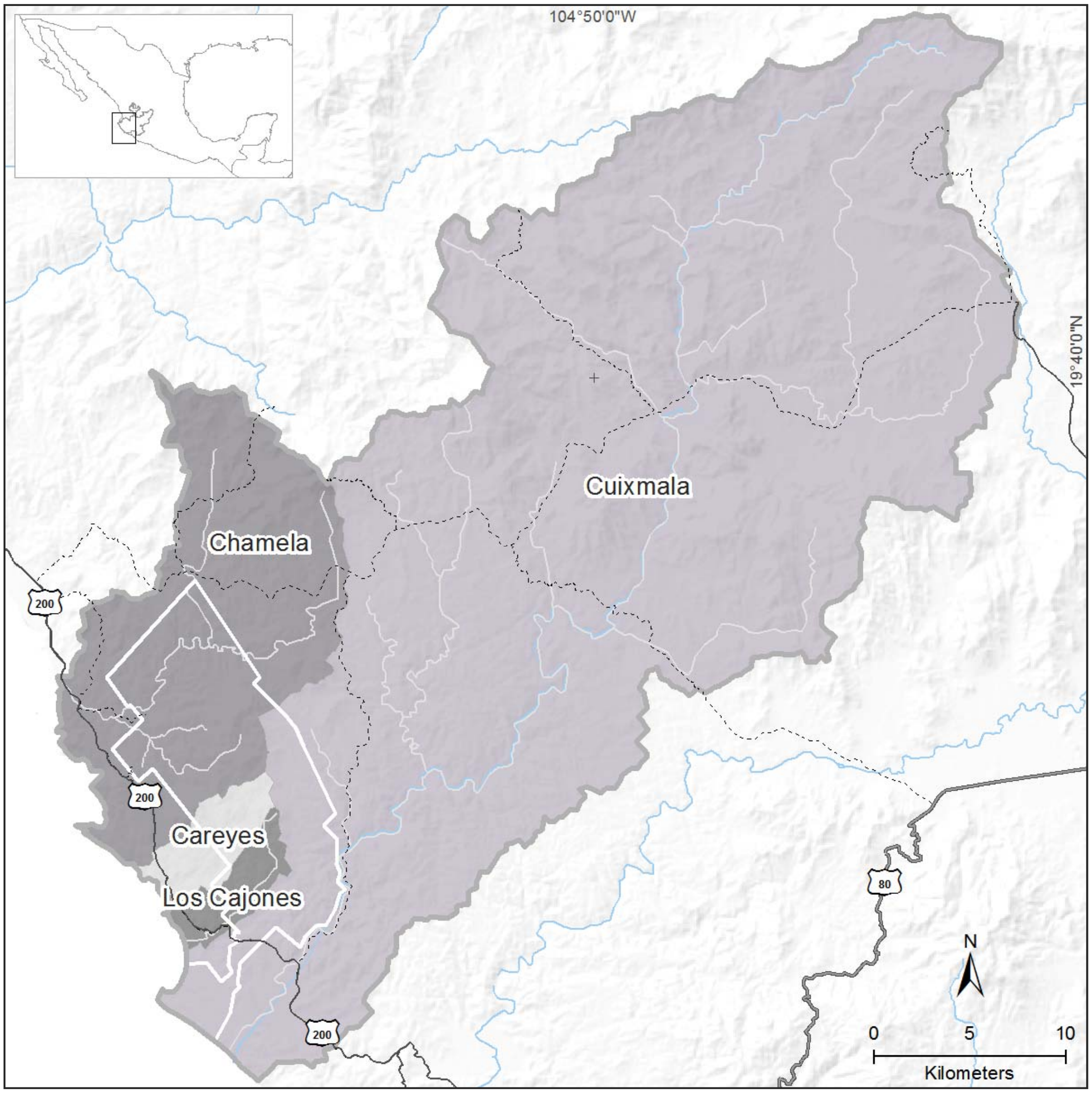

Figure 2.1 Map of the study area including the Chamela-Cuixmala biosphere reserve (shown in white) and the four sub-basins (Chamela, Careyes, Cuixmala and Los Cajones).

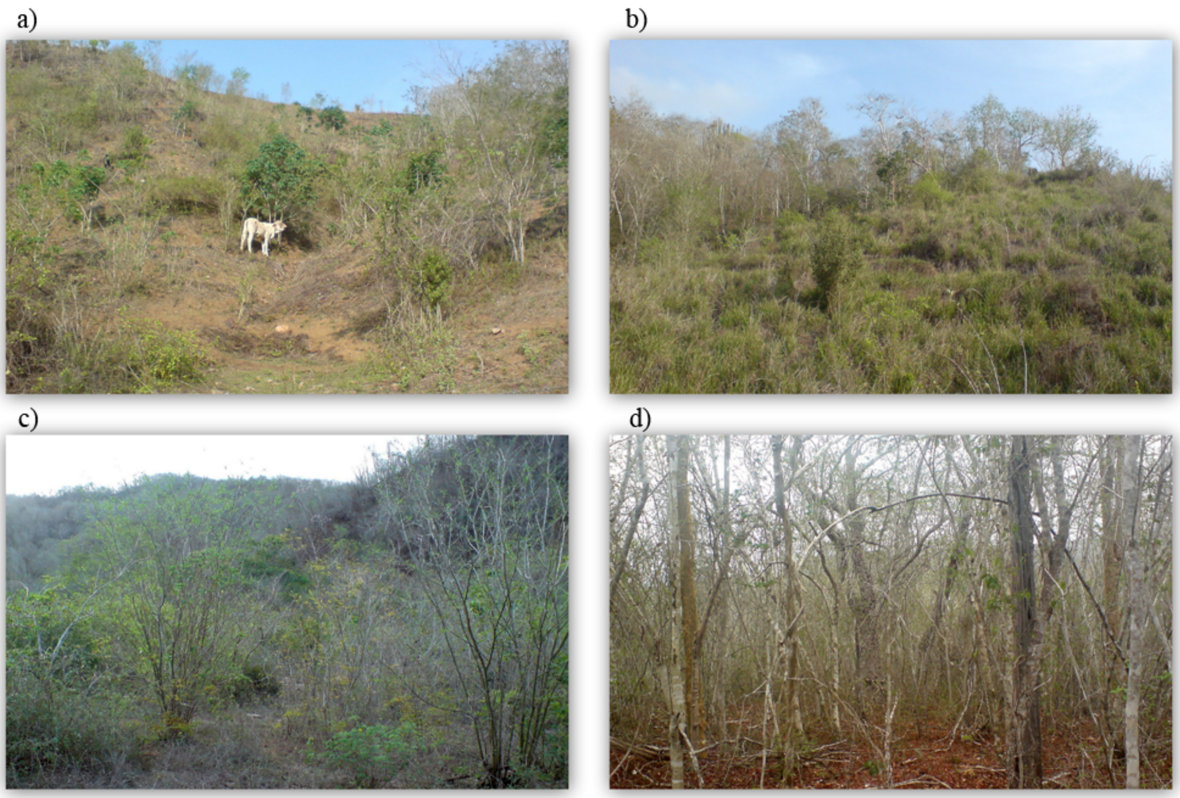

Figure 2.2 Photographs showing four land cover types defined as:

a) Pasture, b) early tropical dry forest, c) intermediate tropical dry forest and d) late tropical dry forest. Pastures occupy 200 Km^2 of the study (15%) representing the biggest threat to the ecosystem. All photos were taken during the dry season in 2010.

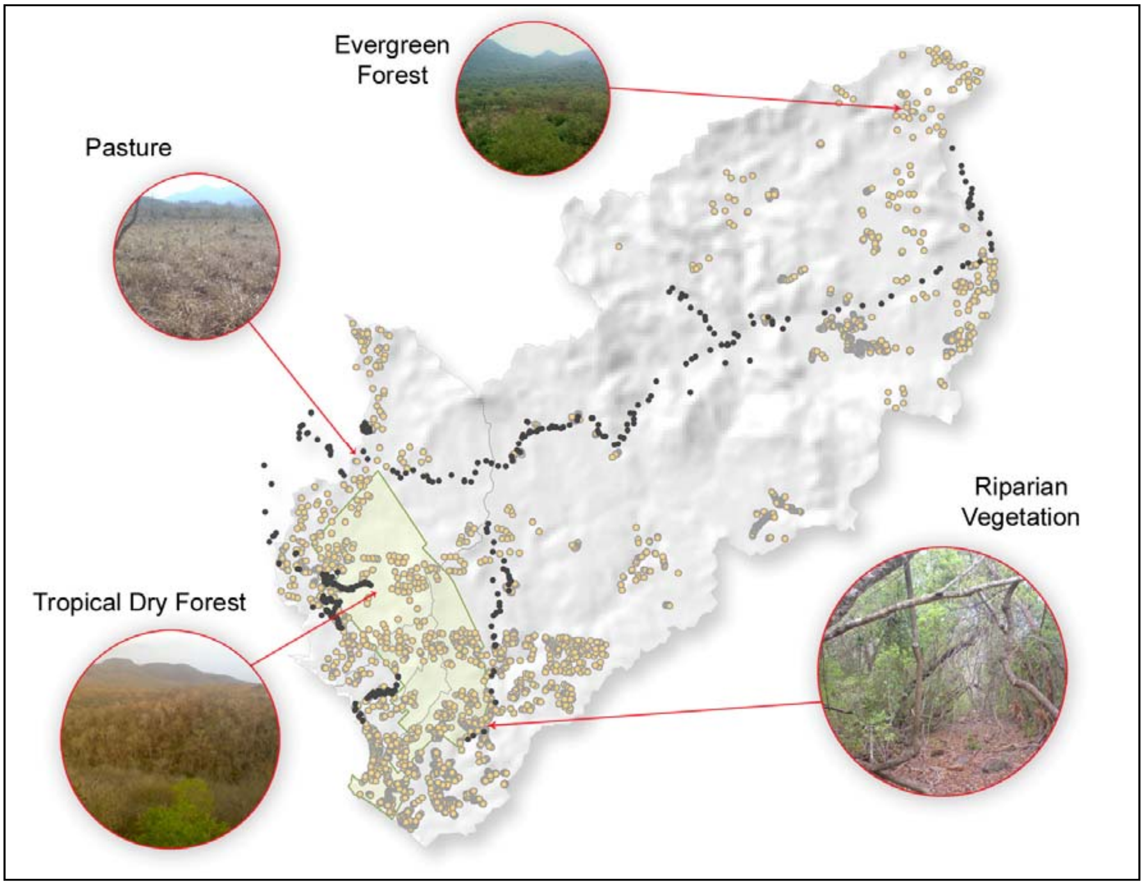

Figure 2.3 Collection of training points during 2010 (dry season). Black markers depict GPS measurements accompanied by photographs. Orange markers represent surrogate training sites collected from high resolution imagery.

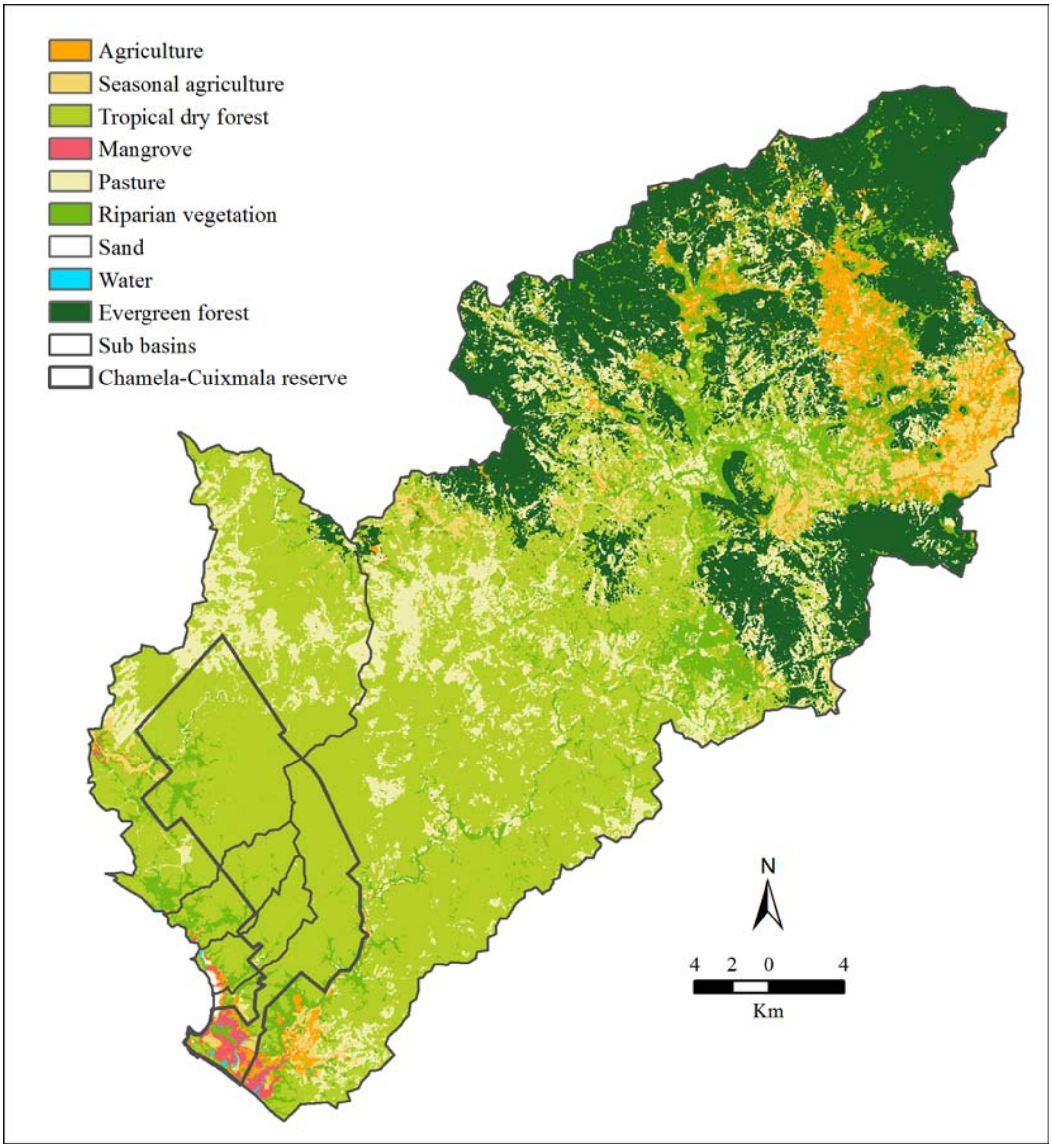

Figure 2.4 Map of the Chamela-Cuixmala land cover in 2006 (15m resolution). The map shows the result of a data mining classification derived from ASTER visible bands and vegetation indices and a digital elevation model from the Shuttle Radar Topography Mission.

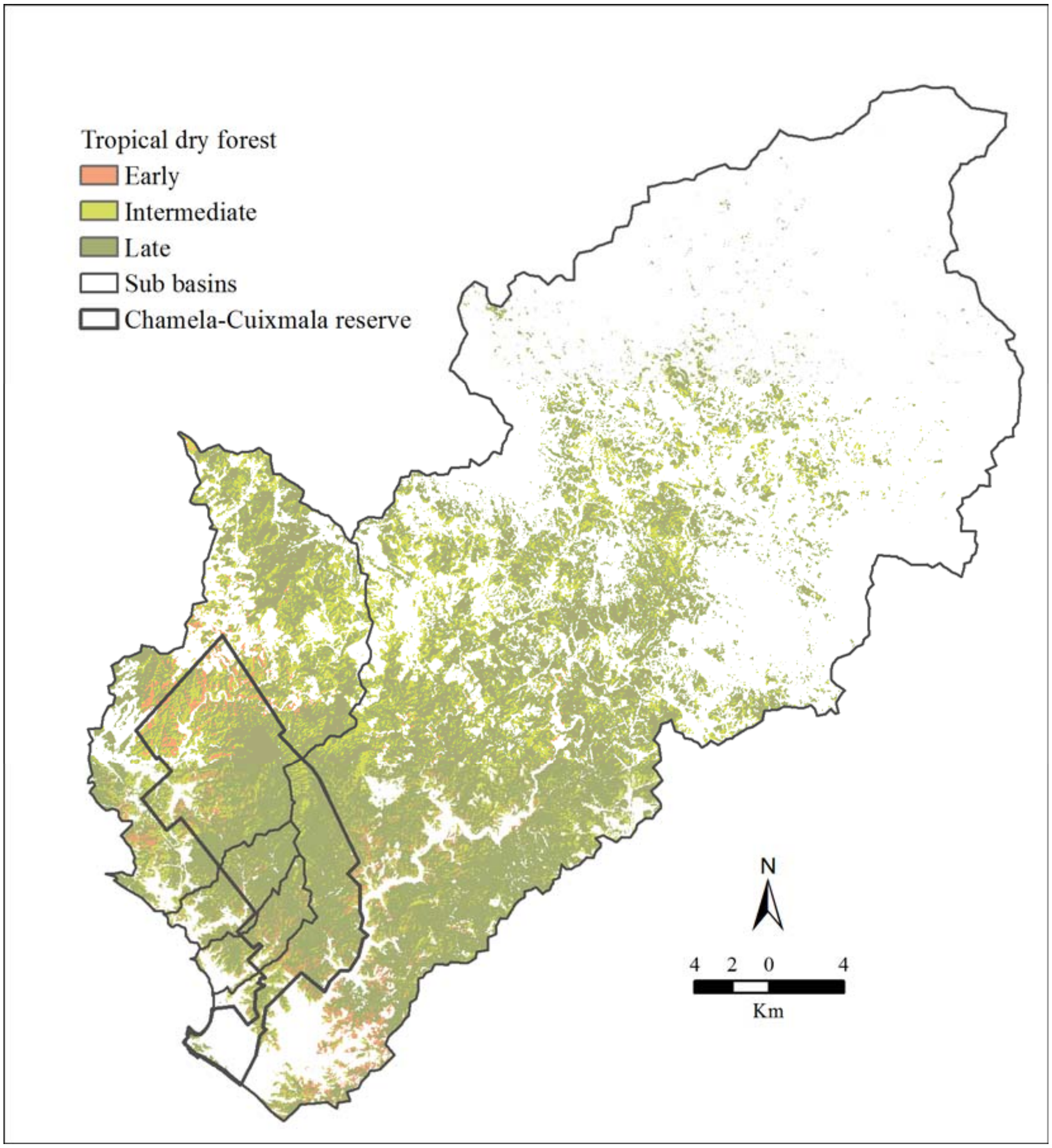

Figure 2.5. Map of the spatial distribution of tropical dry forest in Chamela, including stages of succession for the year 2006. Other types of vegetation were not included in order to facilitate visualization of dry forest patches.

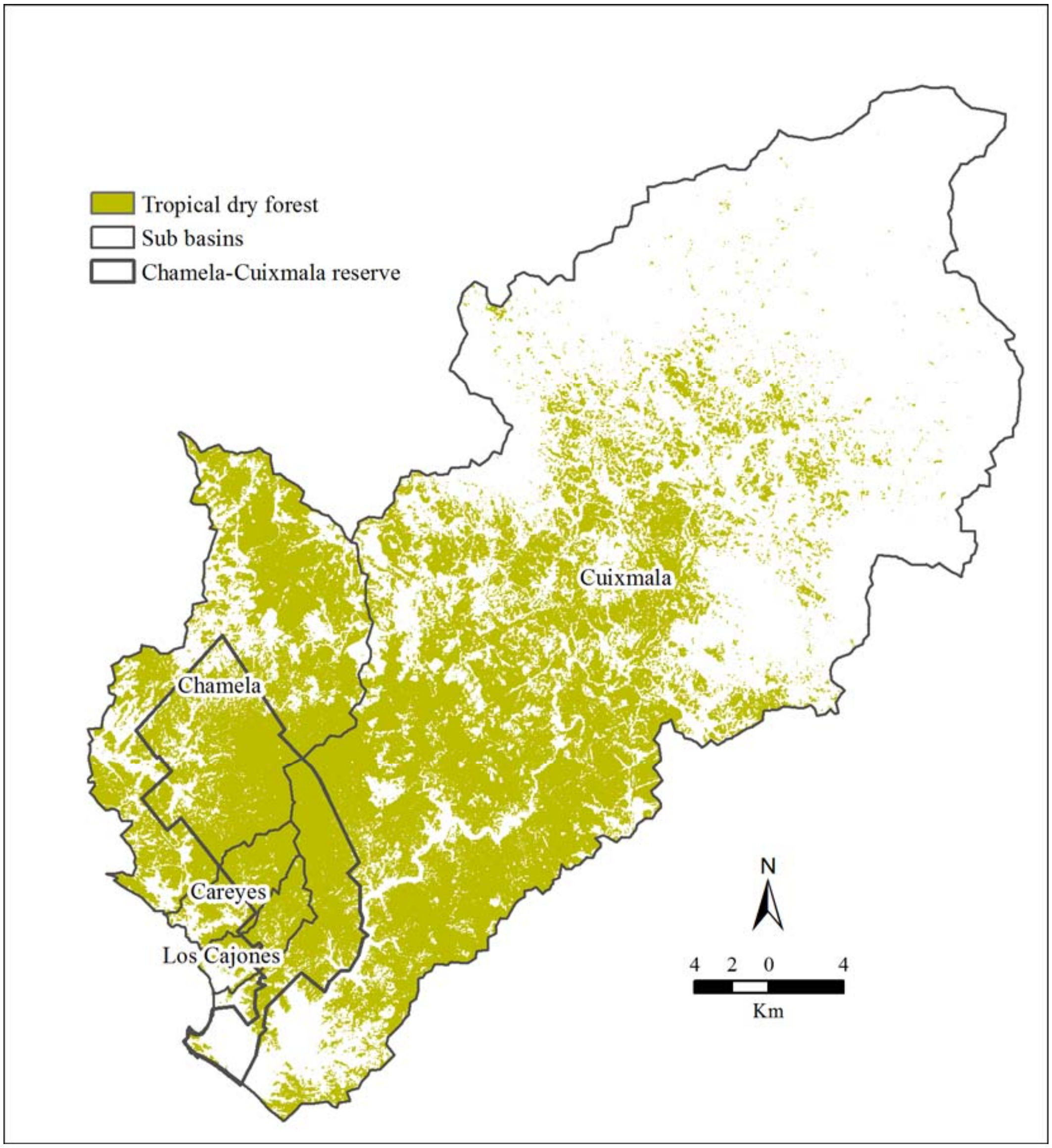

Figure 2.6 Overview map showing the tropical dry forest distribution across the Chamela-Cuixmala region. Note that the tropical dry forest becomes fragmented southeast and northwest of the reserve, as well as towards the northeast of the Cuixmala basin.

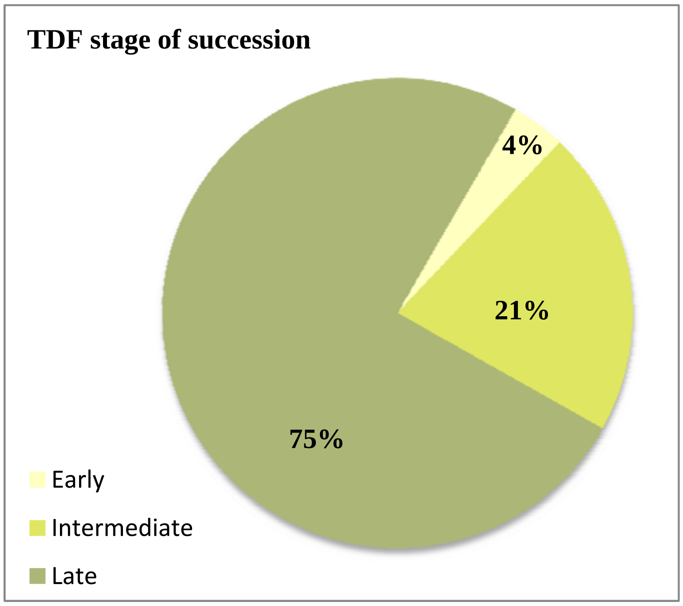

Figure 2.7 Tropical dry forest distributions per successional stage. An estimated 75% of the total dry forest in the region is over 50 years old. Only a small percentage of tropical dry forest if between 3-5 years old (early stage).

TABLES

Table 2.1 Image data sources.

SENSOR	Spatial Resolution	Scene ID	Temporal Resolution	Year
ASTER	15m	Path: 30 Rows: 46,47	On-demand	2006
SRTM	90m	3 N19 W106 3 N19 W105	N/A	2000

Table 2.2 Land cover estimates with percentage area. The most abundant land cover class is represented by tropical dry forest, followed by evergreen forest and pasture. About 25 percent of the area has been transformed into pasture and agricultural fields. There are about 2.2 km^2 of developed land along the Chamela-Cuixmala Basin.

Class	Vegetation type	Area estimation (Km^2)	Mean accuracy	% Area estimation
1	Agriculture	54.87	89.73	4.06
2	Seasonal agriculture	60.60	89.84	4.49
3	Tropical Dry Forest	580.23	99.02	42.95
4	Mangrove	6.15	89.40	0.46
5	Pasture	202.70	96.98	15.00
6	Riparian	135.91	93.86	10.06
7	Beach	0.99	98.34	0.07
8	Water	0.78	88.34	0.06
9	Evergreen forest	308.44	92.00	22.83
10	Urban	0.42	77.50	0.03
Total		1351.10	91.50	100

Table 2.3 Error matrix used to validate the Chamela-Cuixmala land cover map. Overall top accuracies were obtained from the decision tree analysis. The overall kappa statistic was equal to 0.90

Land cover	Class	1	2	3	4	5	6	7	8	9	10	TOTAL	Accuracy
Agriculture	1	47	0	0	3	0	0	0	0	5	0	55	85%
Seas. Agric.	2	0	49	0	0	1	0	1	0	0	9	60	82%
TDF	3	0	0	50	0	1	0	0	0	0	0	51	98%
Mangrove	4	0	0	0	46	0	0	0	7	0	0	53	87%
Pasture	5	0	1	0	0	48	0	0	0	0	0	49	98%
Riparian	6	3	0	0	1	0	50	0	0	3	0	57	88%
Beach	7	0	0	0	0	0	0	29	0	0	0	29	100%
Water	8	0	0	0	0	0	0	0	23	0	0	23	100%
Evergreen	9	0	0	0	0	0	0	0	0	42	0	42	100%
Urban	10	0	0	0	0	0	0	0	0	0	11	11	100%
	TOTAL	50	50	50	50	50	50	30	30	50	20	430	
	Accuracy	94%	98%	100%	92%	96%	100%	97%	77%	84%	55%		92%

Table 2.4 Error matrix showing users and producer's accuracy for the tropical dry forest successional stages map. Overall kappa statistic = 0.76

Stage	Class	1	2	3	TOTAL	Accuracy
Early	1	21	1	0	22	95.45%
Int.	2	7	26	1	34	76.47%
Late	3	2	3	29	34	85.29%
	TOTAL	30	30	30	90	
	Accuracy	70%	87%	97%		84.44%

Table 2.5 Area estimates of tropical dry forest successional stages. The majority of combined tropical dry forests are located along the Cuixmala sub basin. Tropical dry forest distributions by percentages are shown to emphasize the importance of each sub basin in dry forest conservation scenarios.

Sub Basin	Early (Ha)	Intermediate (Ha)	Late (Ha)	TOTAL TDF (Ha)	Sub basin (Ha)	% TDF Land Cover basin	% TDF distribution
Chamela	963.90	4096.30	10791.07	15851.27	21649	73.21%	27.72%
Careyes	48.76	210.02	1608.50	1867.28	2238	83.43%	3.26%
Los Cajones	96.59	225.36	1159.00	1480.95	1817	81.50%	2.59%
Cuixmala	1042.02	7515.52	29418.79	37976.33	109298	34.74%	66.42%
TOTAL	2151.27	12047.20	42977.36	57175.83	135002	42.35%	100%

CHAPTER 3. MODELING TROPICAL DRY FOREST PHENOLOGY

INTRODUCTION

Satellite derived information has been used widely to monitor key earth surface processes over large areas (Reed and Brown, 2005). The manifold effects of changes in vegetation dynamics due to anomalies in climate have become a priority in research over the past decades (Fontana et al., 2008). Among these, changes of phenological patterns (induced by climate change) present an issue of concern to the scientific and decision making community (Chen et al., 2004; Goetz et al., 2005). Though that regional climate changes have been extensively documented, and compiled since the third Intergovernmental Panel on Climate Change report (IPCC), the effects of climate change in developing countries are poorly documented, challenging the knowledge of its consequences for natural resources and human health. Remote sensing has proven to help understand these patterns at the global and local levels, as well as their response through time (Archibald and Scholes, 2007; Jensen, 2007; Reed and Brown, 2005).

Land surface phenology describes the seasonal variation of vegetation measured by a remote sensor (White and Nemani, 2006). Land surface phenology differs from traditional plant phenology (green up, flower boom; leaf senescence) in that it is observed remotely. It also presents combined data at a spatial resolution determined by the sensor configuration, allowing us to monitor vegetation dynamics over large areas continuously over time (Ganguly et al., 2010). Phenology observations have been used to document patterns in vegetation, water and carbon balance as key indicators of climate change (Soudani et al., 2008).

Tropical Dry Forest (TDF) is the most transformed and unprotected of the large tropical ecosystems (Quesada and Stoner, 2004). Currently there are less than 520,000 Km^2 of Tropical Dry Forest in the Americas (Portillo-Quintero and Sanchez-Azofeifa, 2010). Dry forest research has received less attention in comparison with tropical rain forest (TRF) derived from institutions and political reasons including the lack of funding. Also, Tropical Dry Forests are the preferred ecosystem for agricultural practices and urban development (Sanchez-Azofeifa et al., 2005). Scientific efforts have been carried out to learn how Tropical Dry Forests responds to anthropogenic pressure and climate change. However, the knowledge of Tropical Dry Forest is still at the early stages.

In Tropical Dry Forests the seasonal growth of plants is determined by moisture related with the timing and amount of rainfall (Bullock, 1986; Quesada et al., 2009). Seasonal changes in the landscape are particularly dramatic with variations throughout the year. During the dry season, the majorities of plant communities lose their leaves and have developed strategies to cope with the hot and dry periods, such as the development of photosynthetic stem and modified leaves for protection and heat dissipation as encountered in species that can tolerate dry conditions such as *Bursera grandifolia* (Aguilar and Noguera, 2002).

Recent studies have shown that Mexico has warmed up over the past three decades (Pavia et al., 2009). Increments in diurnal temperatures have occurred at a rate of 0.16°C per decade (Peralta-Hernandez et al., 2009). Such observations could be related to the severe droughts observed in the tropics since the 1970’s (IPCC, 2007). In the Chamela-Cuixmala region, rainfall patterns are the biophysical parameter controlling leaf production (Martinez-Yrizar and Sarukhan, 1990). Thus, the long term effects of changing environmental conditions need to be investigated in order to understand the ecosystem response through time.

Mapping the activity and development of vegetation is challenging since it requires continuous measurements of multiple variables including temperature, precipitation, soil moisture, relative humidity and remote sensing data. In order to succeed in such a difficult task, a wide variety of methods have been developed. Direct methods include field measurements of organic matter (litterfall) recordings of budburst observations, ground based field spectroscopy and micrometeorological towers. Methods for the quantification of net primary production such as fine root production and litterfall are considered the most accurate for implicit reasons and proximity to vegetation (Martinez-Yrizar et al., 1996), with the disadvantage of demanding large amounts of resources and time. In addition, direct methods are expensive and limited to small spatial resolutions. In contrast, empirical methods derived from remote sensing (satellite measurements) provide a wide range of applications. These include the development of vegetation indices to track vegetation dynamics, and the use of proxy ecosystem variables (temperature, precipitation, and land use/cover change) to develop models that describe ecosystem functionality. These methods have the advantage of covering vast areas up to global coverage, low cost of most satellite products, and continuous measurements to maintain time series analysis. Important conditions for the application of the remote sensing approach for phenology observations include user dependency, rigorous validation (against other data sources such as field measurements) and user's expert knowledge of the area.

Observation of trends by land cover class illustrates at a small scale how ecosystems respond to environmental conditions (Bradley and Mustard, 2008). Although short term regional changes are believed to have their origin from land use changes (Parmesan and Yohe, 2003). Altering the timing and extent of phenological parameters including the start of season, length of the growing season and length of the dry season could promote adverse effects on ecosystem functionality at different scales. From plant communities up to weighty and complex ecosystem interactions between energy and matter, affecting biomass production, local hydrologic cycles and hence, food production.

Alterations in the length of the growing seasons are difficult to understand in terms of their implication for land processes (Archibald and Scholes, 2007). Martinez-Yrizar and Sarukhan (1990) observed that the majority of the trees in the Chamela-Cuixmala reserve stay leafless for at least six months (except inverse phenology threes and riparian vegetation).

Regional phenology can be affected by complex spatio-temporal variations from precipitation, altitude, soil type and floristic composition to anthropogenic activities such as land management practices (Zhang et al., 2003; Zhang et al., 2005). Studies have shown that Tropical Dry Forest productivity in the Chamela biological station is higher at the valley sites than on hilly terrain such as slopes and mounts (Martinez-Yrizar and Sarukhan, 1990). Such observations provide an overview to investigate alternative techniques for ecosystem phenology response to landscape features. In terms of vegetation development, remote sensing phenology parameters such as the length of the growing season can be used for proxy estimations of biophysical interactions, plant development, ecosystem productivity and energy fluxes (Ganguly et al., 2010) that can be also related to interannual climate variations.

PHENOLOGY RESPONSE TO CLIMATE CHANGE

Climatic factors such as temperature and precipitation can be linked to land cover and phenology (Heumann et al., 2007; Zhang et al., 2006). Remote sensing observations of an early start of the season have been related to positive trends of temperature for northern latitudes (Maignan et al., 2008). In contrast a delay of the start of the growing season has been reported for the intertropical zone (Zhang et al., 2007), thus, changing patterns in vegetation development. In Mexico raising temperatures have been observed for the past four decades (Pavia et al., 2009; Peralta-Hernandez et al., 2009). An analysis of climate related vulnerabilities for Mexico show a climate change scenario with temperature increments of 3.5°C (dry season) and 2.3°C (growing season) and 1% increment in precipitation for the Chamela-Cuixmala region (Magana et al., 1997). Variations in air surface temperature over Mexico have been related to changes in vegetation development (Englehart and Douglas, 2005).

Recently, positive trends in vegetation greenness (NDVI) were detected via remote sensing (MODIS and AVHRR) including central Mexico (Fensholt and Proud, 2012). Nevertheless such efforts are often focused in areas with strong seasonality and at the continental level, yet the effects in Tropical Dry Forests remain poorly investigated, especially at the local scale. In semiarid regions of Africa, the seasonal development of vegetation (including Tropical Dry Forest) shows a strong relationship with the timing of the rainy season (Zhang et al., 2005). Given the precipitation patterns described for the Chamela-Cuixmala region, the Tropical Dry Forest is expected to face a severe drought during the next decades. Since the year 2000, the Terra and Aqua satellites provide continuous measurements at moderate resolution that can be suitable for monitoring the spatial distribution of phenology and the timing of the seasons in the Chamela region.

PHENOLOGY PARAMETERS

Long term satellite derived time-series are valuable to understand the impacts of climate on land surfaces. A vast number of studies have reported shifts in vegetation seasonality (Fontana et al., 2008; Heumann et al., 2007; Reed and Brown, 2005) in northern latitudes, attributing alterations in vegetation phenology to climate change

(Badeck et al., 2004; Chen et al., 2004). Modifications of plant development include longer growing seasons (Karlsen et al., 2008), and the appearance of early spring and late autumn (Myneni et al., 1997; Studer et al., 2007). Major climate anomalies have been correlated with early and late onsets of vegetation (Maignan et al., 2008).

The Normalized Difference Vegetation Index (NDVI) is a commonly used vegetation index in climate-phenology studies (Fontana et al., 2008). It quantifies the contrast between red surface reflectance (rRED), which decreases as the chlorophyll content increases, and the near-infrared surface reflectance (rNIR), which increases with growing leaf area index and crown coverage (Beck et al., 2007). The MODIS enhanced vegetation index (EVI) was developed to optimize vegetation signal, with improved sensitivity in high biomass regions and reduced atmospheric and soil background noise (Ratana et al., 2005). The EVI has been reported to be more responsive to canopy structural variations, including leaf area index (LAI), canopy type, plant physiognomy, and canopy architecture. It also maintains sensitivity even in high leaf area index canopies (such as the Amazon) by exploiting the attributes of near infrared canopy reflectance that are less likely to saturate in high LAI conditions, particularly with the use of moderate resolution satellite imagery (Huete et al., 2002).

Several phenological parameters such as the start of the growing season (SOS), end of the growing season (EOS), length of the growing season (LGS) and the length of the dry season (LDS) can be measured via remote sensing time series. The method consists in finding a threshold in the vegetation index time series where the values exceed a defined target value (Bradley and Mustard, 2008; Jonsson and Eklundh, 2002).

Common challenges in the quantification of remote sensing phenology include errors in the data from multiple origins. Among them are differences between Biomes, proximity to urban features, agriculture, anthropogenic practices, natural disturbances and mixed signals, making it difficult to obtain a satisfactory quality signal without performing data cleaning (White et al., 2005). A solution to this problem consists in applying a smoothing algorithm to satellite time series with the possibility to include weighted quality information from the sensor. This method has been implemented in a program called TIMESAT (Jonsson and Eklundh, 2002; Jonsson and Eklundh, 2004), which can be used to derive the timing of the vegetation parameters of the start of the growing season, end of the growing season, length of the growing season, seasonal amplitude and the small integral of the function (SINT). These parameters are essential bioclimatic indicators for modeling complex vegetation-climate interactions (Soudani et al., 2008).

TIMESAT has been used in a long term remote sensing phenology analysis in the African Sahel to discuss trends in the SOS and EOS (Heumann et al., 2007) and to detect anomalies in vegetation phenology over Northern Europe (Beck et al., 2007). Start of season estimations can be obtained from satellite time series by measuring a point in time where the NDVI exceeds certain inflection points or where the increment begins to accelerate (Bradley and Mustard, 2008). It is possible to calculate other phenology parameters such as SOS, EOS and LGS using thresholds in time-series of vegetation indices (Jonsson and Eklundh, 2002). Karlsen et al. (2008) calculated the EOS as the time where NDVI values went below 0.95 of the mean value and the SOS as the increment over 0.85 of the NDVI mean value. In TIMESAT, the parameters for SOS and EOS can be adjusted by the user according to vegetation types, since those values can vary between ecosystems and geographic location. This method works best at the local scale where vegetation types are homogeneous with a few regional components (Zhang et al., 2006).

The availability of continuous land surface spectral measurements have allowed the scientific community to monitor regional changes in plant phenology. Research efforts have been focused in correcting the effects of bare soil, and atmospheric particles that introduce noise in satellite derived vegetation index time series (Huete et al., 2002). Underlying the importance of research focused on the effects of the environment and physical conditions (such as canopy background) in vegetation indices (Heumann et al., 2007). In remote sensing studies, seasonal integrated vegetation indices have been related to net primary production (Heumann et al., 2007; Jonsson and Eklundh, 2002).

SHIFTS IN PHENOLOGY

The effects of climate variability on ecosystems have in recent decades become increasingly urgent, within the global climate change discussion. Earlier start of spring and extended autumn can be observed in phenological time series resulting in prolonged growing seasons (Fontana et al., 2008). Continuous measurements of surface reflectance have produced several studies addressing changes in vegetation phenology worldwide. White et al. (2005) catalogued the world's most representative ecosystems in terms of their spectral signal into “pheno-regions”, including sites with strong annual cycles. Suggesting that observed changes in phenology originated from climate change rather than locally driven changes. However, Tropical Dry Forests were not considered in the study.

Satellite time series have also been used to characterize phenological variability. For instance, Bradley and Mustard (2008) detected phenological trends over the principal land cover classes of the Great Basin in the United States using Advanced Very High Resolution Radiometer (AVHRR) data. NDVI time-series from AVHRR have shown the complexity of the parameters involved in phenology. Reed and Brown (2005) found shifts in the EOS related to land use changes in southern Canada, while in the Arctic EOS variations were attributed to climate change. Also in the northern hemisphere, recent warming trends have shown to be the cause of earlier spring and later autumn (Goetz et al., 2005; Studer et al., 2007).

MODIS DROUGHT OBSERVATIONS

Remote sensing phenology requires continuous observations over extended periods of time. For instance, interannual phenology variations in coniferous forests have been described by remotely sensed imagery at moderate resolution (Fisher and Mustard, 2007), proving the usefulness of such information and its suitability for modeling the effects of climate change on ecosystems. Despite the existence of suitable applications, there is a clear need to emphasize ground data generation as a requirement for continuous validation. In terms of regional phenology Prasad et al. (2007) explored spatial variations of NDVI within different ecosystems, including Tropical Dry Forest, attributing most variations to species composition. Nevertheless, vegetation phenology studies often exclude a clear explanation of the effects of fragmentation, drought, and vegetation structure, leaving a significant knowledge gap in the study of regional phenology.

Rain forest and temperate ecosystems have caught the attention of phenology research in the tropics. There is a lag in the ratio of 1:300 research papers for Tropical

Dry Forest compared to tropical wet forest (Sanchez-Azofeifa et al., 2005). Therefore, Tropical Dry Forest research has become an urgent matter that needs immediate attention. Although Mexico is experiencing a significant drought since the past few decades (Stahle et al., 2009). Currently, no regional studies in Tropical Dry Forest using remote sensing have properly addressed phenology. The ecological implications of warming processes in Mexico are still unknown, raising the question of how climate change will affect water production and ecosystem services in the future.

This research aims to address the following questions about the spatial relationship between Tropical Dry Forest phenology and climate change in the Chamela-Cuixmala region:

What is the influence of Tropical Dry Forest structure in vegetation processes under different climate conditions?

What is the relationship of plant communities with water availability throughout the Chamela-Cuixmala basin?

What is the spatial distribution of ecosystem productivity? How this does relates to successional stages of Tropical Dry Forest? How will changes in forest structure and phenology affect ecosystems services in the future?

OBJECTIVES

In the context of the current body of literature and identified knowledge gaps, the main goal of this thesis is to produce the first spatiotemporal analysis of the Tropical Dry Forest in the Chamela Cuixmala Biosphere reserve, focusing on regional phenology as a function of land cover (successional stages of Tropical Dry Forest). The exercise describes the seasonality of vegetation at two spatial resolutions: regional scale (1:250,000) and plot level (1:30,000).

To explore the biophysical interactions of Tropical Dry Forest through analysis of satellite derived phenology as an empirical method to monitor vegetation activity (Solano et al., 2010) in the Chamela-Cuixmala region.

The estimation of Tropical Dry Forest key seasonality parameters, including the start of the growing season, end of the growing season, length of the growing season, length of the dry season and ecosystem productivity for the years 2000-2011 via satellite time series from the Moderate Resolution Imaging Spectroradiometer.

This research will document the seasonal development of the Tropical Dry Forest in the Chamela-Cuixmala region and will describe the phenology response of three key stages of succession (early, intermediate and late). Further, I aim to perform a seasonal trend analysis for each phenology parameter at the landscape and plot level scale. Field productivity data from a collaborative project will be compared against productivity data from the satellite for two vegetation indexes, the Enhanced Vegetation Index (EVI) and the Normalized Difference Vegetation Index (NDVI).

METHODS

Remote sensing phenology is the only mean to assess surface dynamics over large geographic areas. Moderate resolution satellite information provides continuous measurements of the landscape, making it suitable for monitoring the seasonal development of vegetation (Ganguly et al., 2010). In this case, satellite time series from the Moderate Resolution Imaging Spectroradiometer (MODIS) were analyzed to evaluate Tropical Dry Forest phenology at the Chamela-Cuixmala Biosphere Reserve. The MODIS sensor on board of the Terra satellite from NASA, continuously measures the land surface at 36 spectral bands (0.4μm-14.4μm) with a spatial resolution of 250m, 500m, 1Km and 0.05 degrees since the year 2000 (Nassar et al., 2008; Solano et al., 2010). The new atmospheric correction in this sensor brings an improved technique to reduce the effects of atmospheric scattering, as encountered in older sensors such as AVHRR (Fontana et al., 2008). The MODIS MOD13Q1 vegetation index (VI) was obtained through NASA's online Earth Sciences Discovery Tool Reverb ECHO.

The selected product MOD13Q1 (table 3.1) with a spatial resolution of 250m uses a robust method to determine green vegetation based on the red (620-670 nm), near infrared (841-876 nm) and blue (459-479 nm) bands (Huete et al., 2002). MODIS Vegetation Indices have been atmospherically corrected for molecular scattering, aerosols and ozone absorption (Olofsson et al., 2007).

The MODIS vegetation index product includes both NDVI and EVI tiles with scene coverage of 1200Km by 1200Km. The NDVI was designed to normalize NIR to red reflectance ratio, between -1 and +1. On the other hand, the EVI incorporates atmospheric effects to account for aerosol scattering and soil background by including a feedback term (Solano et al., 2010). An improved layer included in the MOD13Q1 product is the summary quality layer, which contains pixel by pixel reliability, where the image bits are organized in 5 main groups starting from fill data (-1), good data (0), marginal data (1), snow covered (2) and cloudy (3).

In order to describe the phenology of the dry forest, we analyzed MODIS data using TIMESAT. The program can estimate phenological parameters with high accuracies (Jonsson and Eklundh, 2002). We worked with the key seasonality parameters of the start of the growing season (SOS), end of the growing season (EOS), length of the growing season (LGS), length of the dry season (LDS), seasonal amplitude and ecosystem productivity (shown in figure 3.1) for the period of 2000-2011. Estimations of seasonal productivity have been related to the cumulative effects of plant growth, represented by the small integral of the fitted function in TIMESAT (Jonsson and Eklundh, 2004).

Satellite productivity from MODIS data was compared using the Pearson correlation coefficient against litterfall data from Tropi-Dry (CIECO-UNAM) as a proxy for field ecosystem productivity. The temporal resolution available for this analysis corresponded to the period of 2005 to 2008 (table 3.2). Three plots for each successional stage of Tropical Dry Forest were included (figure 3.2). The year 2007 was excluded due to missing litter fall data.

Studies of Tropical Dry Forest phenology at the landscape level were performed for the Chamela Cuixmala region. We extracted MODIS pixels with 80% or more Tropical Dry Forest cover from a 15 meter resolution map (figure 3.3) previously generated during the land cover analysis. The tropical dry forest selection method utilized zonal analysis performed in ArcGIS. The inputs to the model consisted on a MODIS mesh as the sampling region and a land cover map derived from an ASTER scene. Further we calculated the selected phenology parameters using TIMESAT. The resulting landscape phenology from MODIS was reported by successional stage.

Climatic information from the Chamela region was included as a reference framework about the local conditions occurring during the period of 2000-2010. We analyzed monthly temperature and precipitation data (figure 3.4) from the Chamela biological station. The data was processed using the non parametric Mann-Kendall seasonal test for trend (Gilbert, 1987; Helsel and Hirsch, 2002). This test was also applied to each of the phenology parameters in order to explain variations in vegetation development. The Mann-Kendall test has demonstrated to provide reliable measurements while using multitemporal data for global change research (Li et al., 2011).

Further, phenology parameters including the dates of occurrence of the start of season, end of season, length of the growing season, length of the dry season and ecosystem productivity, were analyzed in terms of their frequency distribution. The analysis was implemented in MATLAB, inspecting each phenological observation to better visualize data distributions as suggested in Boschetti et al. (2009).

In addition, maps of regional phenology were generated in TIMESAT and later registered (spatial alignment) using ERDAS. The maps were created for both vegetation indices (NDVI and EVI). The final phenology maps of the Chamela Cuixmala region included the five studied phenological parameters (SOS, EOS, LGS, LDS and Productivity).

PHENOLOGY QUANTIFICATION

Vegetation index time series were processed by fitting a double logistic function in TIMESAT. This smoothing approach has been used to reduce data errors due to clouds and sensor geometry (Jonsson and Eklundh, 2002). TIMESAT fits every pixel in the time series with a moving window, extracting phenological parameters for each encountered season. It is possible to account for missing pixels and noisy data (spike removal), thus allowing effective control over the function. It is also possible to set minimum and maximum levels to process the data and determine the adjustment strength of the function (Jonsson and Eklundh, 2004). The time series processing used weighted MODIS measurements derived from a pixel quality information band (figure 3.5). The use of weights was defined as 1, 0.5 and 0 assigned to pixels with reliability values of 0 (Good), 1 (Marginal/usable) and 3 (Cloudy) respectively.

The length of the dry season was derived using TIMESAT dates of the start and the end of the growing season, calculated in ERDAS using the following formula:

$$LDS = SOSs_2 - EOSs_1$$

Where $SOSs_2$ corresponds to the beginning of the growing season (the following year) and $EOSs_1$ corresponds to the end of the growing season (the previous year) in a given phenological year.

The use of a threshold in the vegetation index to determine the start of the growing season, end of the growing season and to estimate other phenological parameters is critical to remote sensing phenology. Current studies have proposed several parameters to calculate the beginning and the end of the growing season. For example in temperate regions, White and Nemani (2006) established a criterion for geographic areas with similar climate known as pheno-regions. Boschetti et al. (2009) described a method for rice crop monitoring and Reed and Brown (2005) used a delayed moving average for the season's curve. Nevertheless, the implementation such methods are rarely used for tropical dry forests. The threshold adjusted for Chamela-Cuixmala was derived by comparing metrics of both MODIS EVI and MODIS NDVI with field observations made by a collaborative research study from Tropi-Dry at the Centro de Investigaciones en Ecosistemas (CIECO) of the National Autonomous University of Mexico (UNAM). Using a threshold locally adapted to the seasonal amplitude (Jonsson and Eklundh, 2002; Jonsson and Eklundh, 2004).

Settings for the start and end of the growing seasons can be adjusted in TIMESAT for each land cover class. For instance, higher values have shown better performance in large regional applications (continental level analysis) and small threshold values for local analysis with a few land cover classes (de Beurs, 2008). The assignment of a value that better represented the start of the growing season and end of the growing season in Chamela was made by comparing satellite with field NDVI (from a phenology tower). The field NDVI was acquired at the Centre for Earth Observation

Sciences (CEOS) of the University of Alberta. The beginning and end of the growing seasons were captured by plotting a double logistic curve on each of the time series. A threshold of 30% change was estimated from the left and right minimum-maximum values.

The smoothing parameters for TIMESAT were estimated through curve fitting in ten random pixels, and using the best performing values for all pixels. This method allows the creation of the best possible fit along an area of study, preventing errors associated with poor adjustments based on a single pixel estimate (Heumann et al., 2007).

SATELLITE DERIVED PHENOLOGY

The MODIS vegetation indices allowed us to perform tropical dry forest analysis with a temporal resolution of 12 years (from 2000 to 2011). The research data set included 230 MODIS images. The imagery was converted from the native EOS HDF format into TIMESAT ready binary files. This approach was accomplished using a combination of the MODIS reprojection Tool v.4 and ERDAS Imagine applications.

A color ramp based on the Jenks natural breaks was selected to visualize the differences in tropical dry forest phenology. This method of thematic map display was selected due to its characteristic of grouping distributions in the best possible combination to emphasize several classes (Luan et al., 2011).

GIS ANALYSIS

A digital elevation model (DEM) was used to bound the watershed and sub basins of the biosphere reserve. The data consisted of two Shuttle Radar Topography Mission (SRTM) images (Jarvis et al., 2008) at a spatial resolution of 90 meters. The images were sink filled in ArcGIS and mosaicked in ERDAS. Topographic boundaries were delineated using a hydrology model in ArcGIS. The process included four steps listed as: 1. The fill tool in ArcGIS locates sinks in the data (due to errors) and fixes the holes using an iteration method. 2. Flow direction. This process creates a raster image indicating the direction of flow based on neighboring cells (Jenson and Domingue, 1988). 3. Flow accumulation. The model takes as input a flow direction raster image and creates a flow accumulation raster image from weighted accumulated cell values flowing down slope (Jenson and Domingue, 1988). 4. Watershed creation. Defined as the area upslope that contributes water flow to a concentrated drainage (ESRI, 2010). The watershed tool in ArcGIS calculates the areas contributing to the watersheds from direction and accumulation layers. The minimum number of cells can be specified according to local features such as ravines and streams. This process can be repeated to define the desired watershed boundaries according to user defined attributes. The final step consisted on converting the raster watershed into a vector format and the generalization of lines following a defined area size by a clipping mask (corresponding to the study area). The resulted hydrologic basin represented an update to existing hydrologic definitions for Mexico described by the Mexican National Institute of Ecology (INE, 2010).

FIELD ESTIMATIONS AND MODIS DATA

Field data was available for the years 2005 to 2008 and consisted in ecosystem productivity normalized as litterfall in Kg/ha. Field data and satellite productivity (integrated EVI and integrated NDVI) relationships were described using a Pearson product moment correlation analysis for each phenological year. This method has been used to compare satellite derived vegetation indices and analysis of global trends (Fensholt and Proud, 2012). The sites selected for correlation analysis included nine MODIS pixels corresponding to nine plots in the field representing each successional stage (early, intermediate and late) with three plots per stage of succession.

RESULTS

On the one hand, the relationship between the start and end of the growing season was better described by the NDVI compared to EVI. The same observation was found for the length of the growing season, length of the dry season and ecosystem productivity at the plot level. On the other hand, the EVI showed more significant trends for the ecosystem productivity at the landscape level (Tau-b = -0.23, Z= -0.93).

Tropical dry forest productivity estimated form the satellite showed a weak relationship with litterfall measurements for all sites and successional stages (figure 3.6). Further a comparison of field and satellite productivity by stages of succession showed a moderate correlation of r^2=0.35 for the NDVI on the early stage of succession and a significant correlation for the EVI productivity r^2=0.44 and $p<0.05$ for the late stage (figure 3.7). The rest of the stages were not correlated, and the EVI intermediate stage and NDVI late stage were the least significant.

Significant increments in productivity were observed after the years 2001 and 2005 (figure 3.8). The first four years in the data presented high and low production seasons alternatively. Tropical dry forest productivity showed a negative trend for the years 2002 to 2005, followed by years of successive alternations between high and low productivity reflecting a strong influence of precipitation patterns in the Chamela-Cuixmala region. Our results agree with observations made in the Chamela region by Martinez-Yrizar and Sarukhan (1990) where litterfall studies showed alternations of low and high productivity years consecutively.

PLOT LEVEL ANALYSIS

Plant litter fall averaged measurements showed that the tropical dry forest became more productive as a function of stand age, except for the intermediate stage in 2006 (average productivity 2,214 Kg/Ha) compared to the early stage (2,415 Kg/Ha). Satellite derived productivity from MODIS also showed such pattern at the landscape level (figure 3.9) where the productivity increased as a function of Tropical Dry Forest age. However, this response was not observed at the plot level analysis (figure 3.10).

Satellite derived productivity was significantly related to the length of the growing season for the NDVI, (r^2 = 0.91) and a moderate correlation was found for the EVI (r^2 = 0.59) as shown in figure 3.11.

The mean productivity for the basin was 161,040 (intNDVI) with a standard deviation of 25,305. Our estimation showed that 2001 was the least productive year (109,109) followed by the year 2005 (131,957). For the EVI, the mean productivity was 114,060 (intEVI), standard deviation 17,044. Showing 2005 as the least productive year (87,116) followed by 2001 (91,800). The Enhanced Vegetation Index was better related (r^2=0.65) with satellite estimated precipitation from the Tropical Rainfall Measuring Mission (TRMM) than the Normalized Vegetation Index (r^2=0.41) (Figure 3.12).

Plot level dry forest phenology showed a positive trend for the start of the growing season for the period 2000 to 2011. This was observed in the late and intermediate stages (figure 3.13). No significant trend was observed for the end of the season with the exception of the NDVI for the late stage (figure 3.14). Suggesting that Tropical Dry Forests at the late stage are losing leaves later over time. This phenomena concur with field observations where soil moisture plays a key role in ecosystem productivity (Martinez-Yrizar and Sarukhan, 1990).

Our analysis showed that the duration of the length of the growing season is changing towards a negative trend (Tau-b -0.35). The trend was significant for the NDVI at the intermediate stage of succession (figure 3.15). Moreover, dry season length predicted from NDVI decreased for the late stage only (Tau-b -0.4); whereas the rest of the plots did not show observable trends (figure 3.16).

LANDSCAPE LEVEL ANALYSIS

A summary of the analysis for trend is shown in table 3.3. The results are organized by tropical dry forest stage of succession (early 3-5 years, intermediate 10-15 years and late 50+ years) and spatial level (plot and landscape). We found a positive trend in the start of the growing season over the twelve year period at the landscape level (figure 3.17). The differences for tropical dry forest onset ranged from 20 to 40 days, calculated as the difference from the earliest start of the growing season (2000) and the latest season (2010). Our landscape level trend analysis showed variations for the start of the growing season that were more pronounced at the late successional stage. Variations were present in the order of two weeks. For the early stages, such variations were estimated between 1.7 to 1.9 weeks. The difference between the earliest start of season (2000) and the latest (2010) was 40 days for the late stage of succession.

The variations in the frequency distribution of the start of the season are shown in figure 3.18 for both the NDVI and the EVI. The EVI presented higher variations for up to 20 days in the season start for the year 2010. A latter start of the growing season during 2012 compared to 2000 can be observed in the frequency distribution graph.

A positive trend was found for the End of the growing Season (Tau-b = 0.25). The trend was significant for the early stage of succession measured by the NDVI (figure 3.19) and the EVI intermediate stage of succession (Tau-b = 0.27). The Tropical dry forest also showed a positive trend for seasonal amplitude (figure 3.20). In the Chamela-Cuixmala basin, early stages of succession were characterized by sparse plant coverage, resembling the conditions of semiarid ecosystems. Variations in the End of the growing season were present during the twelve year period (figure 3.21). The year that ended the soonest of all the time series was 2001, followed by 2004.

Estimations for the length of the growing season at the landscape level (figure 3.22) did not show a significant trend the (Z = 0). The regression showed a negative slope for the EVI.

In terms of its frequency distribution, variations in the length of the growing season (figure 3.23) were higher for the NDVI. The years 2003 and 2009 presented longer growing seasons. The shortest phenological years occurred in 2001 and 2005.

The intermediate stage of tropical dry forest showed a negative trend in the length of the dry season (Z = 1.07, Tau-b = -0.28). This trend was also present for the late stage (Z = 1.25, Tau-b = -0.33) as shown in figure 3.24. The negative trend found in the length of the dry season suggests that well established vegetation could retain green canopies better than the early stage. As for the EVI, no significant trends were detected in the Length of the Dry Season (Z < 0.72). Variations in the Length of the Dry Season through the years are summarized in figure 3.25. Our estimations show that the driest seasons occurred in 2001 (189 days), followed by 2004 (183 days) and 2005 (166 days).

Tropical dry forest response to precipitation causes variations in the Length of the Growing Season. In the region, rainfall patterns were affected by tropical cyclones, and major circulation patterns such as El niño and la niña (Maass et al., 2005). Variations in the length of the growing season were higher than in the length of the dry season estimated from NDVI. Such variations occurred in a range up to 80 days for the dry season and 50 days for the growing season.

Our estimations of the length of the dry season showed significant differences between the normalized difference vegetation index (NDVI) and the enhanced vegetation index (EVI). Recent studies have shown a discrepancy between NDVI and EVI derived productivity (Ratana et al., 2005). Our satellite derived productivity showed a negative trend (Tau-b = 0.23 for the early EVI) at the landscape level (figure 3.26). MODIS productivity for the NDVI and EVI indicated that the least productive years were 2001, 2005 and 2010.

The frequency distribution of productivity through the phenology analysis (figure 3.27) showed higher variations for the NDVI. The two vegetation indices showed that the years 2001 and 2005 were the least productive.

SPATIAL DISTRIBUTION OF PHENOLOGY

Delays in the season start of 50 to 60 days were observed in 2001 located in the southeast of the Chamela Cuixmala region (figure 3.28). Both vegetation indices agreed that 2000 was the year with the earlier season start (50 days before the average). The map of the start of the growing season also shows the locations where delays for this parameter were notable during 2005 and 2010.

The maps of the end of the growing season (figure 3.29) show a clear relationship with successional stages. For instance, the season ends in the early stage of succession before the intermediate and late stages. For the year 2001, the NDVI End of Season map showed an abnormal sooner end of the season that along with years of 2004, 2005 and 2009 is distributed near early stages of succession and agricultural sites (marked with a black rectangle). This could be related to the inability of the earlier stages of succession and deforested areas to retain water and stay green over time.

The mapped distribution of the length of the growing season (figure 3.30) showed the extent of the drought for the years 2001 and 2005. The dry conditions were more severe near the early stage of succession and agricultural fields. Overall there was a clear pattern in seasonal development along transitional forest from Tropical Dry Forest to sub deciduous dry forest, near the center of the region (ecotone boundary clearly observed in the NDVI LGS map during 2001 and 2008).

The location of the areas with longer dry seasonality were again in proximity to deforested zones, croplands and early stages of forest succession (figure 3.31) especially for the years of 2001, 2004, and 2009 in the EVI maps.

Ecosystem productivity maps (Figure 3.32) showed the importance of the Cuixmala River as a provider of humidity (and through the ravine network) to support tropical dry forest productivity longer than in areas away from water bodies. Areas near the Careyes stream showed lower productivity and could be related to less discharge encountered in the Careyes sub basin. The Chamela basin showed the lowest season amplitude for during the period 2000-2001 (figure 3.33). This may be associated with low precipitations registered during those years and possibly the proximity to agricultural areas.

The negative slope in ecosystem productivity (figure 3.34) contrasted with the positive slope observed for precipitation and temperature in the Chamela-Cuixmala region. Our estimation of ecosystem productivity showed that the years 2003 (195,177 (intNDVI)) and 2006 (179,743 (intNDVI)) were the most productive for the reserve (mean = 161,040 intNDVI standard deviation = 25,305 intNDVI). In related studies Gomez-Mendoza et al. (2008) reported an extremely dry period during the year 2001. Their observations suggested that vegetation could recover after such extreme droughts responding to precipitation increments in the following years. Our findings coincide in that vegetation responded after the 2001 drought with a subsequent recovery during the next couple of years. Further consideration needs to be taking in to account with regards to dry forest age, health and geographic distribution.

DISCUSSION

Vegetation indices are suitable for the analysis of Tropical Dry Forest phenology because they can separate vegetation cover observations from the rest of land cover classes. Recent studies have proved that MODIS vegetation indices are suitable to systematically observe vegetation development with high accuracies (Boschetti et al., 2009). However, the majority of such studies have been done in larger areas. In the Chamela-Cuixmala Tropical Dry Forest, seasonal productivity depends strongly on water deficit (Martinez-Yrizar and Sarukhan, 1990). Our phenology estimations revealed the highest variations between consecutive seasons for both measurements (EVI and NDVI) observed after a dry year.

The development of vegetation in terms of integrated photosynthetic activity showed a highly variable behavior and dependency from the time and amount of rainfall. The existence of tropical monsoons of an unpredictable nature in the region could explain the variability of satellite derived productivity. It is likely that the environmental force controlling the start of the growing season was soil moisture content. However, other complex vegetation interactions as well as *in situ* conditions (such as the root system), topography and aspect play a decisive role for vegetation development (Maignan et al., 2008).

Our analysis suggested that the late stage of Tropical Dry Forest could sustain leaves over a longer period compared to the intermediate and early stages of succession. Observed increments in seasonal amplitude were related with positive trends in precipitation. Rainfall events appear to be concentrated in fewer days every year (heavy rainfall) as described by (Maass et al., 2005). Such conditions have influenced how Tropical Dry Forest develops over the years. For instance, larger amounts of rainfall occurring in shorter periods reduce the time plants have to grow leaves with negative consequences for the early stages of development, also affecting local crops for agriculture.

Changes in land use practices such as conversion to pastures have shown to drive changes in seasonality (Reed and Brown, 2005). In Chamela, the proximity to agricultural fields and early stages of tropical dry forest appeared to negatively impact regional phenology. Our results support recent studies where net primary production (NPP) was higher in places where woody plants exist (Davison et al., 2011). For instance, composite values of satellite derived productivity increased as a function of successional stage. The observations were consistent through the twelve year period of analysis. Well developed canopies were expected to have greater leaf area index. However, further analysis is needed to assess how the root system contributes to the stability of the ecosystem.

Tropical dry forest seasonality exhibited an oscillatory pattern, highlighting the importance of continuous monitoring efforts in order to have a better understanding of its vegetation dynamics. The consequences of the observed variations in phenology are still poorly documented. It is known for crop production that the length of the growing season is highly dependent of season start, since its timing sets the conditions for plant production (Reed and Brown, 2005; Schwartz, 2003). In the case of Tropical Dry Forest, early and intermediate stages of succession face an increased stress due to changes in temperature and precipitation, which can potentially cause such plant communities to be replaced by semiarid vegetation. The oscillating behavior of the Tropical dry forest productivity could be related to the ecosystem recovery from dry years. For instance improved land management practices appear to positively affect vegetation development, moreover recoveries from drought have been described using NDVI in time series analysis for the Sahel region in Africa (Eklundh and Olsson, 2003).

Our results suggest that the Chamela-Cuixmala tropical dry forests are responding to climatic variations according to vegetation composition. Early stages of Tropical Dry Forest appear to be more susceptible to changing conditions, including precipitation regimes, drought and soil loss; thus preventing the continuity and healthy development of the ecosystem. Late tropical dry forest appeared to be favored by the nature of changes observed in precipitation and temperature. This could be explained due to the ability of mature tropical dry forest’s to retain moisture for longer periods during precipitation delays. Meanwhile, tropical dry forest early and intermediate stages appeared to be more vulnerable to increasing harsh conditions.

Phenology maps depicting the spatial distribution of the end of the growing season show that vegetation in the central region (sub deciduous Tropical dry forest) did not experience an earlier end of the growing season and was able to stay productive longer than the rest of the ecosystem.

Phenology quantification at the landscape level performed better than a single pixel measurement (plot level). This can be due to missing data and mixed signals encountered in single pixels. In contrast, estimates from averaged pixels (landscape level) provided clearer signal yielding improved observations in comparison to plot level analysis.

The geographic location of the Chamela-Cuixmala basin represented a challenging scenario for remote sensing analysis based on the visible light. Clouds were present in up to 60 per cent of the images through each season. Consequently low quality pixels derived from the occurrence of storms of an unpredictable nature, were meticulously filtered to remove noise from the data. The low agreement between satellite and field productivity was attributed to scaling differences and the lack of continuous field measurements. Thus, this study has shown the implications to perform such comparisons and identifies the need for satellite time series validation. Further investigations on the link of light use efficiency models with field measurements are needed to achieve better insights of the seasonal development of tropical dry forest.

The use of proxy phenology to monitor ecosystem productivity is still at the early stages. Garrity et al. (2011) described complications associated with estimations based on spectral measurements only, and the failure to accurately represent net ecosystem exchange trends via satellite observations. However, satellite information such as MODIS is needed for the development of such estimations based on the light use efficiency model (Eklundh et al., 2007). Temporal remote sensing information is recognized as a key element to track the seasonal vegetation development and its relationship with structural land cover characteristics (Badeck et al., 2004; Chen et al., 2004; Jonsson and Eklundh, 2002; Soudani et al., 2008; White et al., 2005). Multiyear ecosystem development trends can be useful to plan for future scenarios in terms of crop production, land cover change scenarios and payment of environmental services.

Remote sensing phenology is a key parameter to understand how ecosystems respond to climate change. This relationship can be used to characterize the extent and magnitude of current impacts and feed current and future climate models. Changes in vegetation seasonality are driven by complex environmental factors, mostly climate. Land use practices and local anthropogenic activities have to contribute to Tropical Dry Forest phenology.

CONCLUSION

The study of seasonal development of vegetation is a fundamental resource for examining the effects of climate change on ecosystems (Parmesan and Yohe, 2003; Reed and Brown, 2005). In order to better understand ecosystem phenology and its variations over time, linking satellite observations with physical data and field observations is strongly needed (Archibald and Scholes, 2007). In the same way, studies using MODIS NDVI have shown to be highly correlated with LAI field measurements (Boschetti et al., 2009). Such projects are sparse in the literature in part due to the absence of continuous field measurements and systematic ecosystem monitoring efforts. This thesis emphasizes the need for continuous monitoring of the tropical dry forest at local scales as a fundamental instrument to validate satellite observations, showing that tropical dry forest disturbances could be monitored via remote sensing while observing changes in regional phenology.

Across the twelve-year analysis of phenology, we found that the tropical dry forests of Chamela exhibited highly variable behavior, most importantly with shifts in the timing of the growing season, length of the dry season and ecosystem productivity.

Overall we found a significant trend towards later start of the season. Moreover, the length of the growing season appears to be decreasing according to EVI observations. The environmental forcing related with current observations included an increase in precipitation concentrated in short events, as well as an increase in the seasonal amplitude. Other sources possibly inducing phenological changes included stage of succession of the Tropical dry forest and land use practices. Our characterization of tropical dry forest phenology in the Chamela region adds to our understanding of regional scale vegetation growth dynamics, identifying the susceptibility of the ecosystem to climate change.

This research represents the first comprehensive satellite-based phenology study in the Tropical Dry Forest of America. The information generated provides a valuable resource contributing to the research on vegetation dynamics, Tropical dry forest structure and implications for ecosystem services. This thesis aims to benefit the decision making community with the knowledge to strengthen tropical dry forest conservation strategies and protect the most endangered of all major ecosystems.

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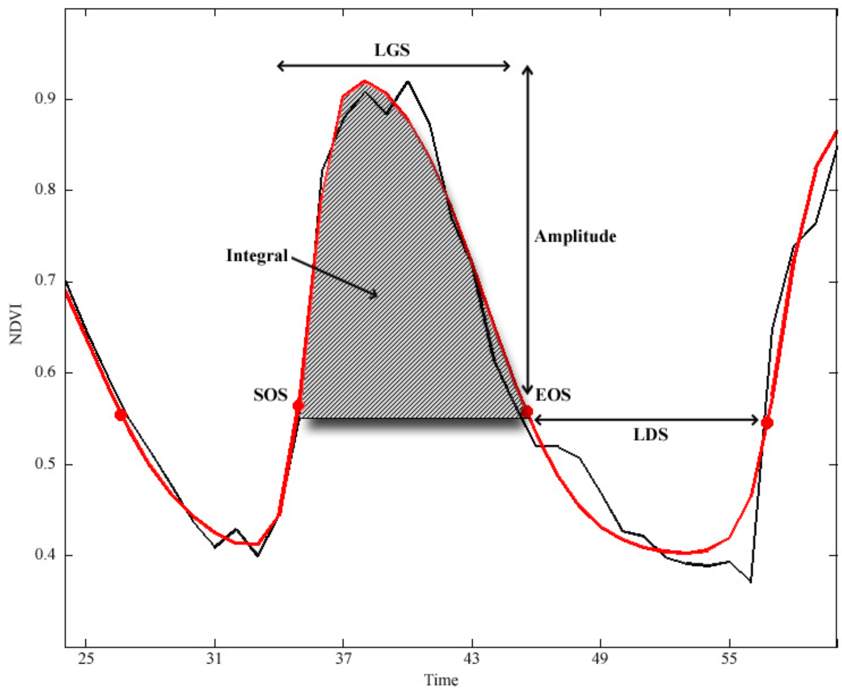


Figure 3.1 TIMESAT seasonality parameters. Start of the growing season (SOS), end of the growing season (EOS), length of the growing season (LGS), small integral (productivity), amplitude and length of the dry season (LDS).

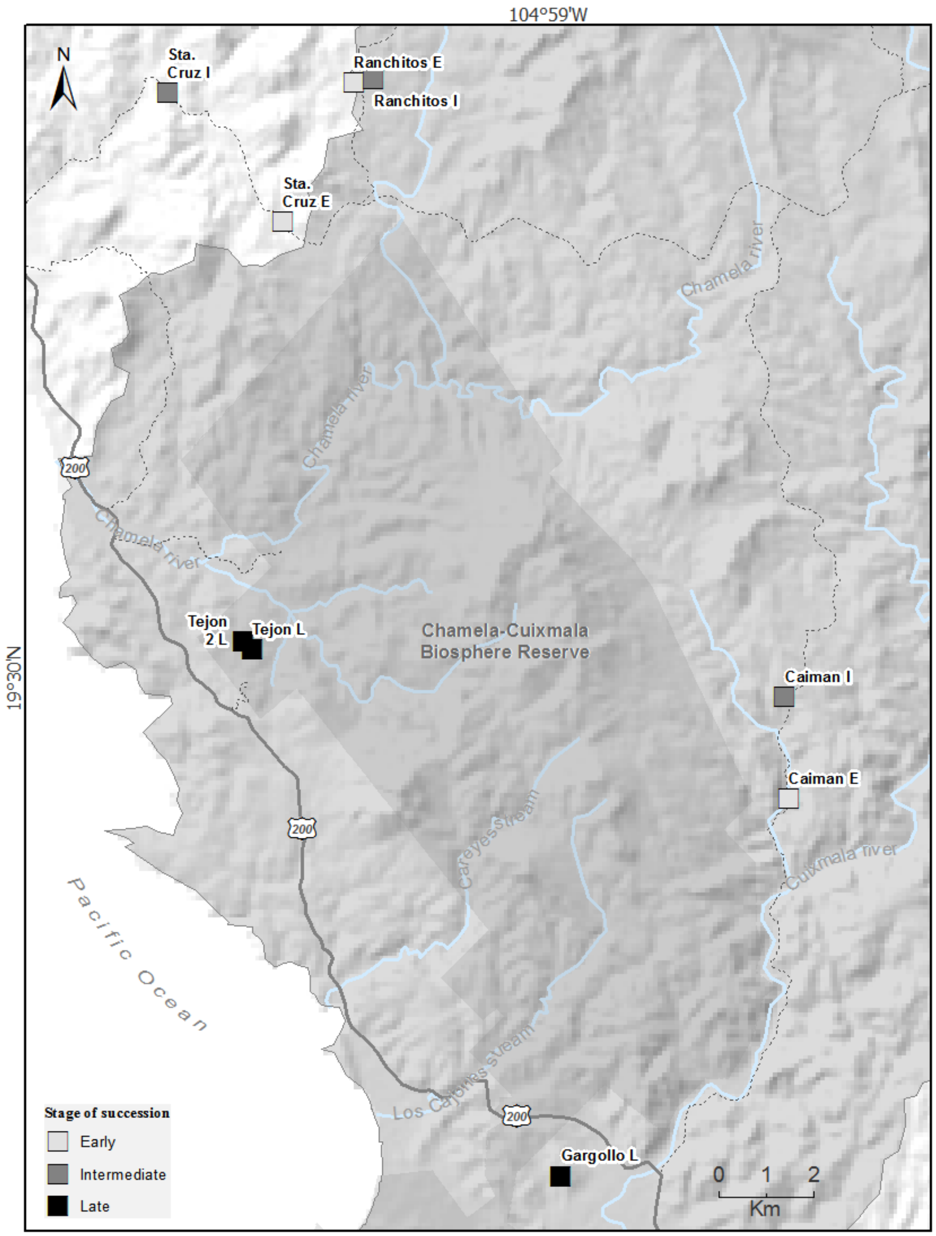


Figure 3.2 Location of the Tropi-Dry field sites and MODIS pixels used for plot level analysis. The MODIS sites were selected at the location of existing litterfall traps.

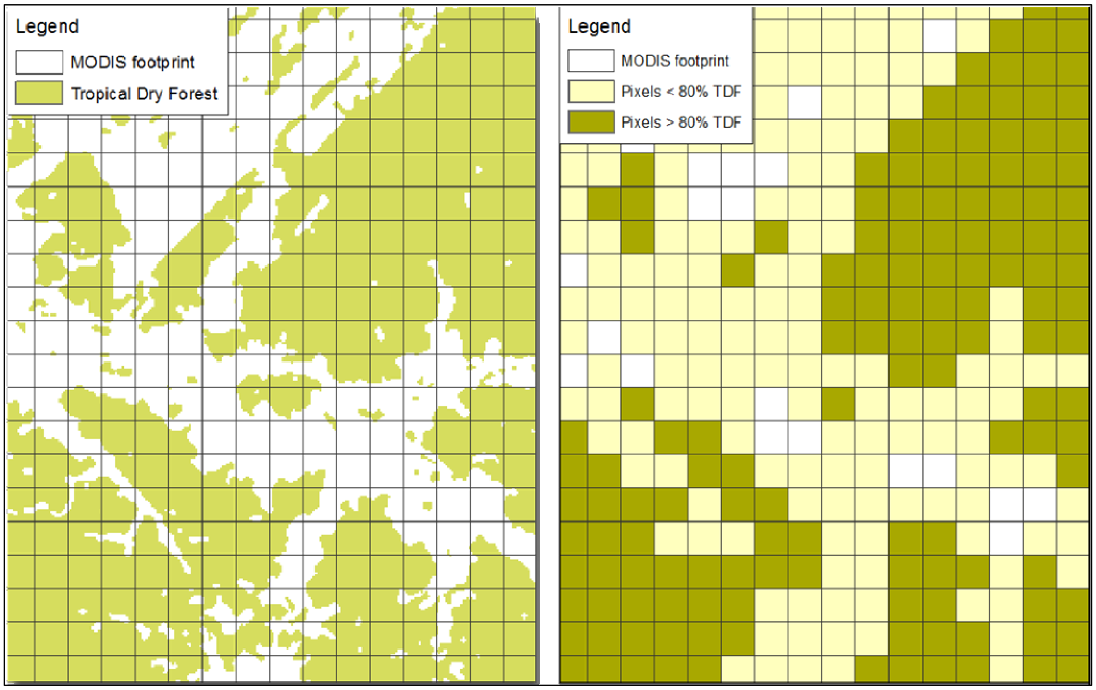


Figure 3.3 ASTER classified image (left) representing tropical dry forest (green) at 15 meters resolution, with a MODIS grid above at 250 meters. Thematic raster (right), showing pixels containing 80% or more tropical dry forest at 250 meters.

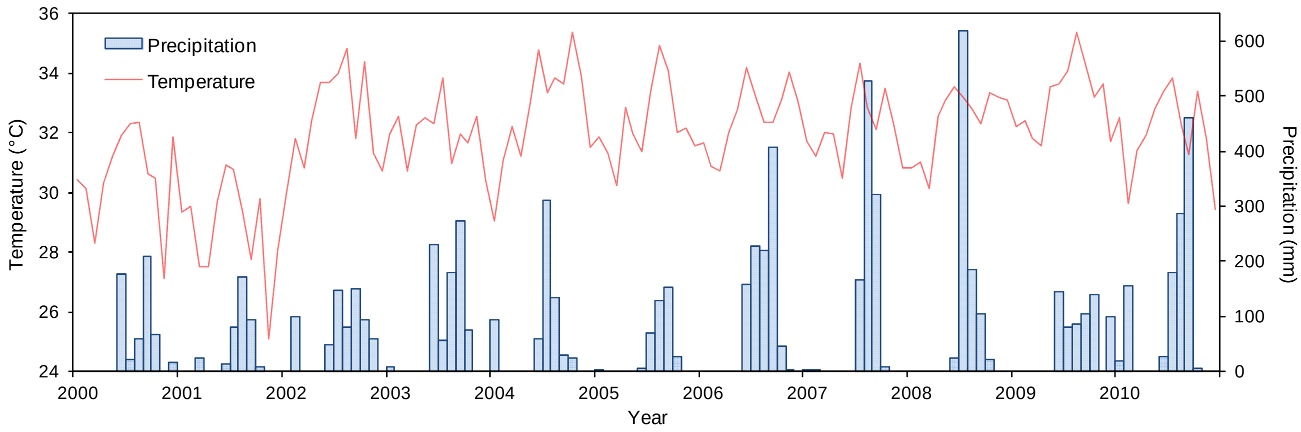


Figure 3.4 Temperature and precipitation observations in the Chamela Cuixmala region for the time of 2000 to 2010. Temperature trends (Tau-b = 0.27, sig. = 0.27, Z = 1.08) and Precipitation trend (Tau-b = 0.38, sig. = 0.11, Z = 1.55).

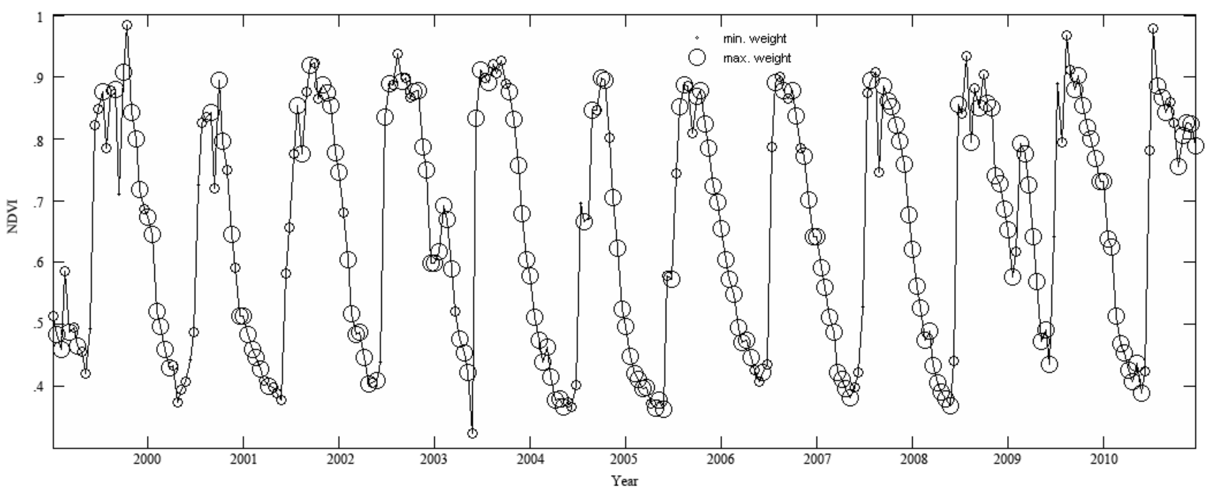


Figure 3.5 Fitted function over MODIS NDVI data using TIMESAT. The use of weights was based on pixel quality information. The size of the ring around each data element is proportional to the assigned weight.

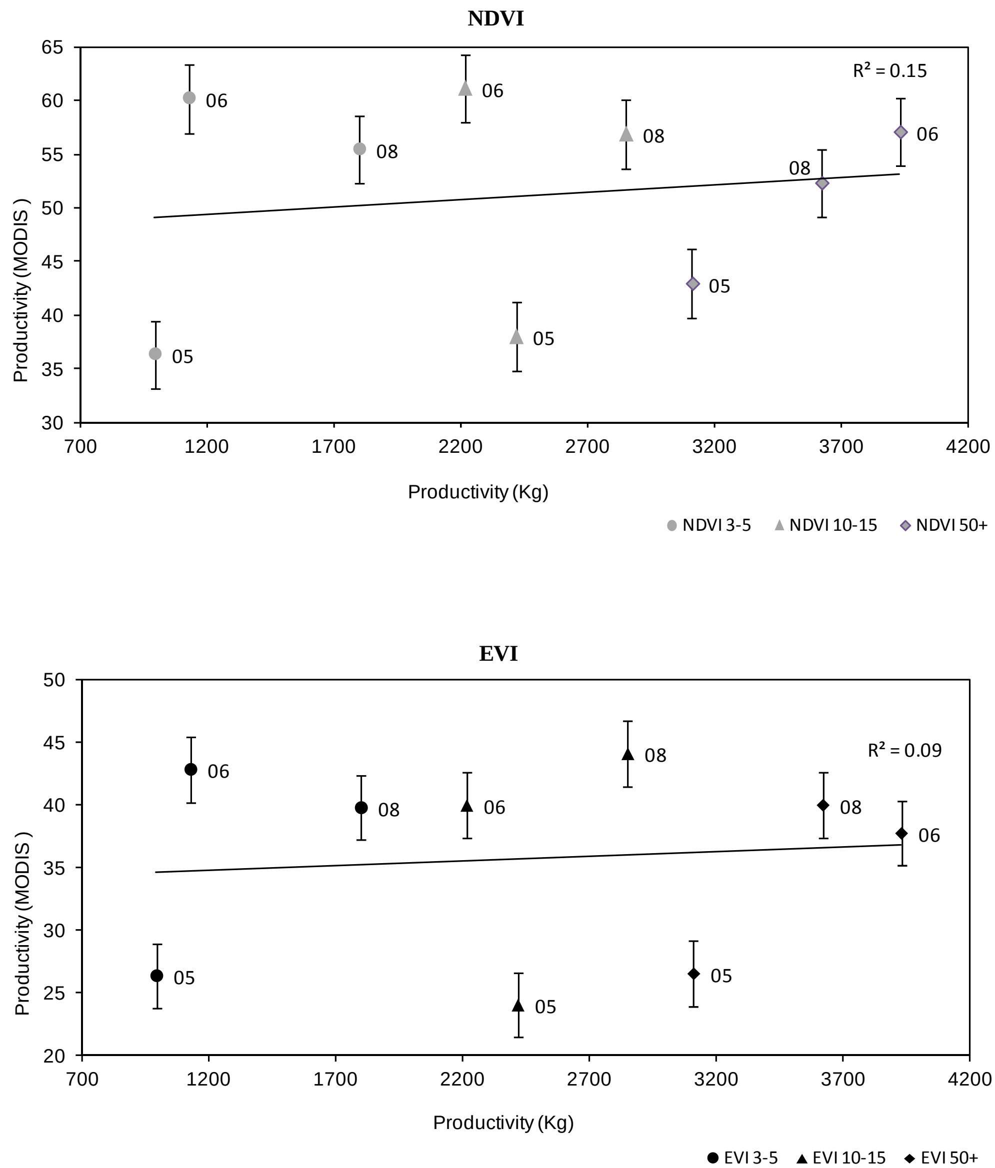


Figure 3.6 Comparison of tropical dry forest productivity from the field and satellite using NDVI (top) and EVI (bottom). Data markers are labelled with the year of observation and Tropical dry forest stage of succession. Early (3-5), intermediate (10-15) and late (50+ years).

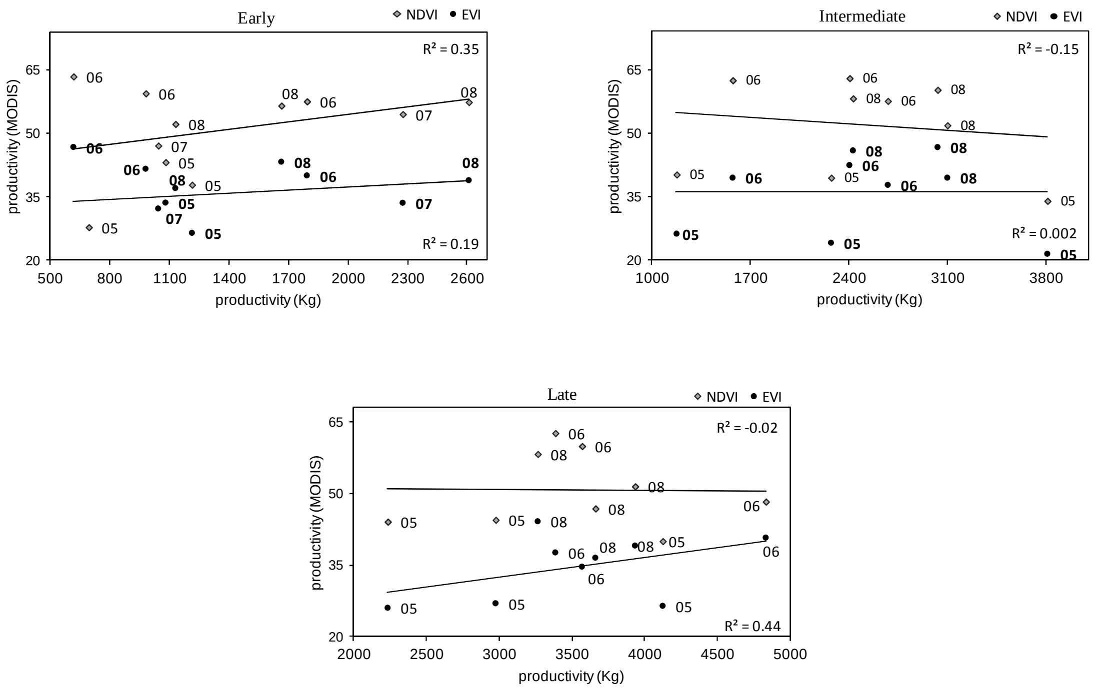
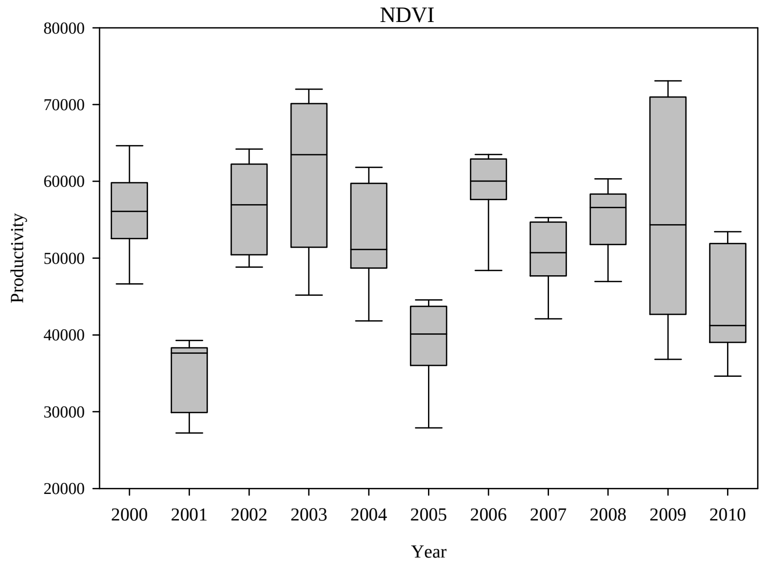


Figure 3.7 Field versus MODIS productivity compared by Tropical dry forest stage of succession. The figure shows a weak to moderate relationship for the early and intermediate stages. However, a moderate correlation was observed for the late EVI (R^2 = 0.44 and $P > 0.05$).



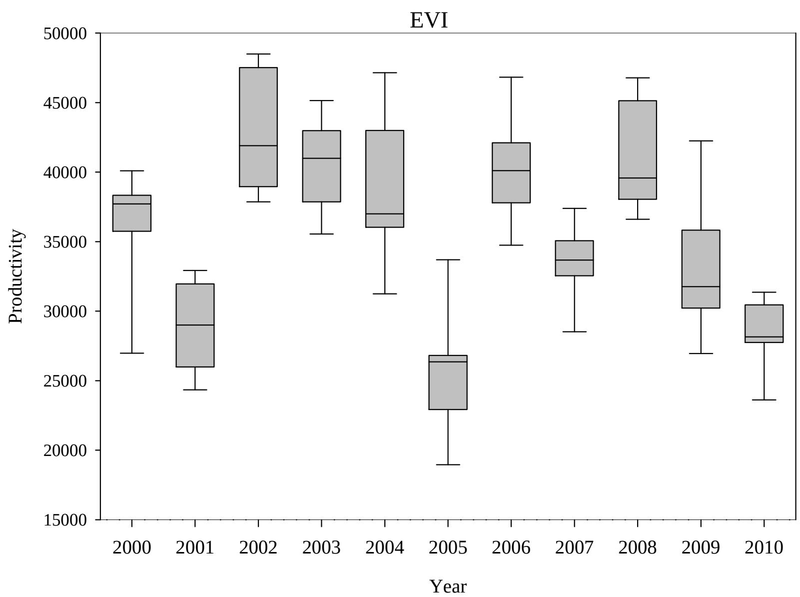


Figure 3.8 Box plot showing all data for the MODIS NDVI and EVI productivity at the plot level for the period of 2000 to 2010. The median is shown as a solid black line.

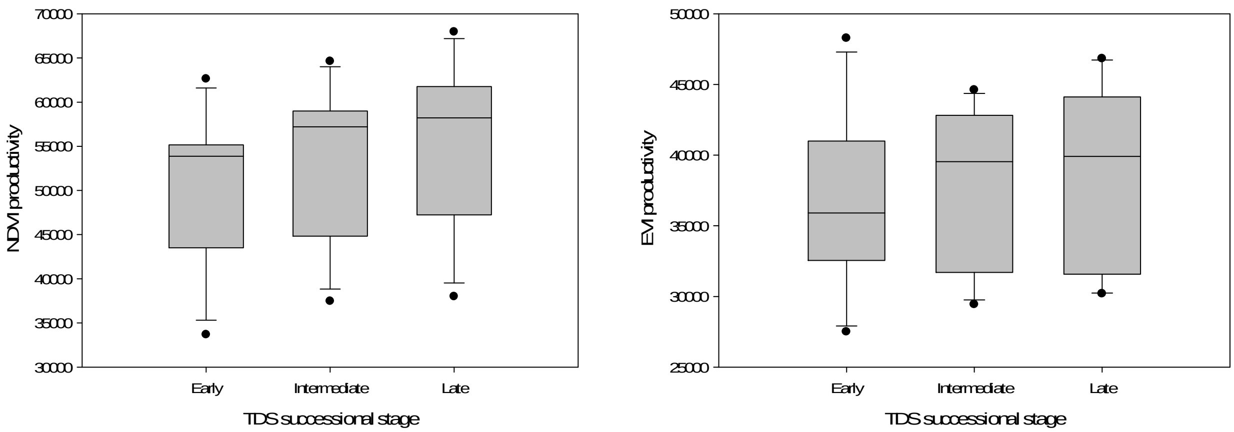


Figure 3.9 Summary of ecosystem productivity at the landscape level for each stage of succession during the period of 2000 to 2010. An increase in productivity was observed from the satellite as a function of stage of succession (old tropical dry forest most productive). Such characteristic was observed only at the landscape level using MODIS data.

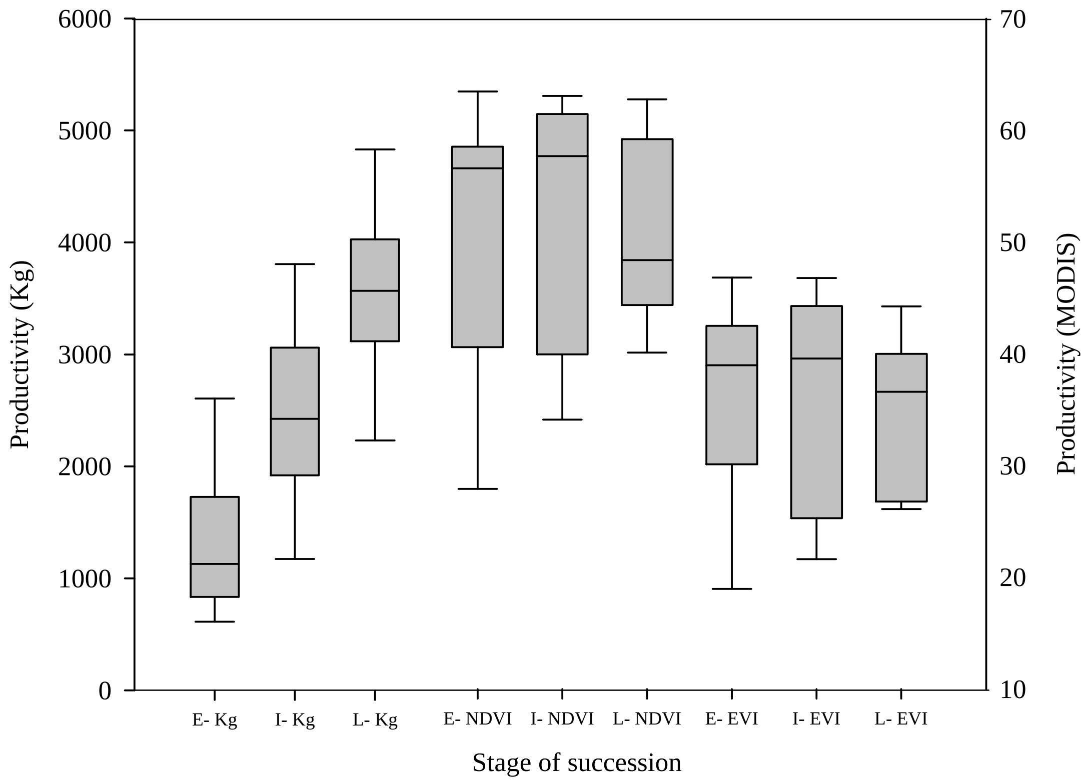


Figure 3.10 Summary of productivity during the years of 2005, 2006 and 2008 by stage of succession at the plot level. Early (E), intermediate (I) and late (L).

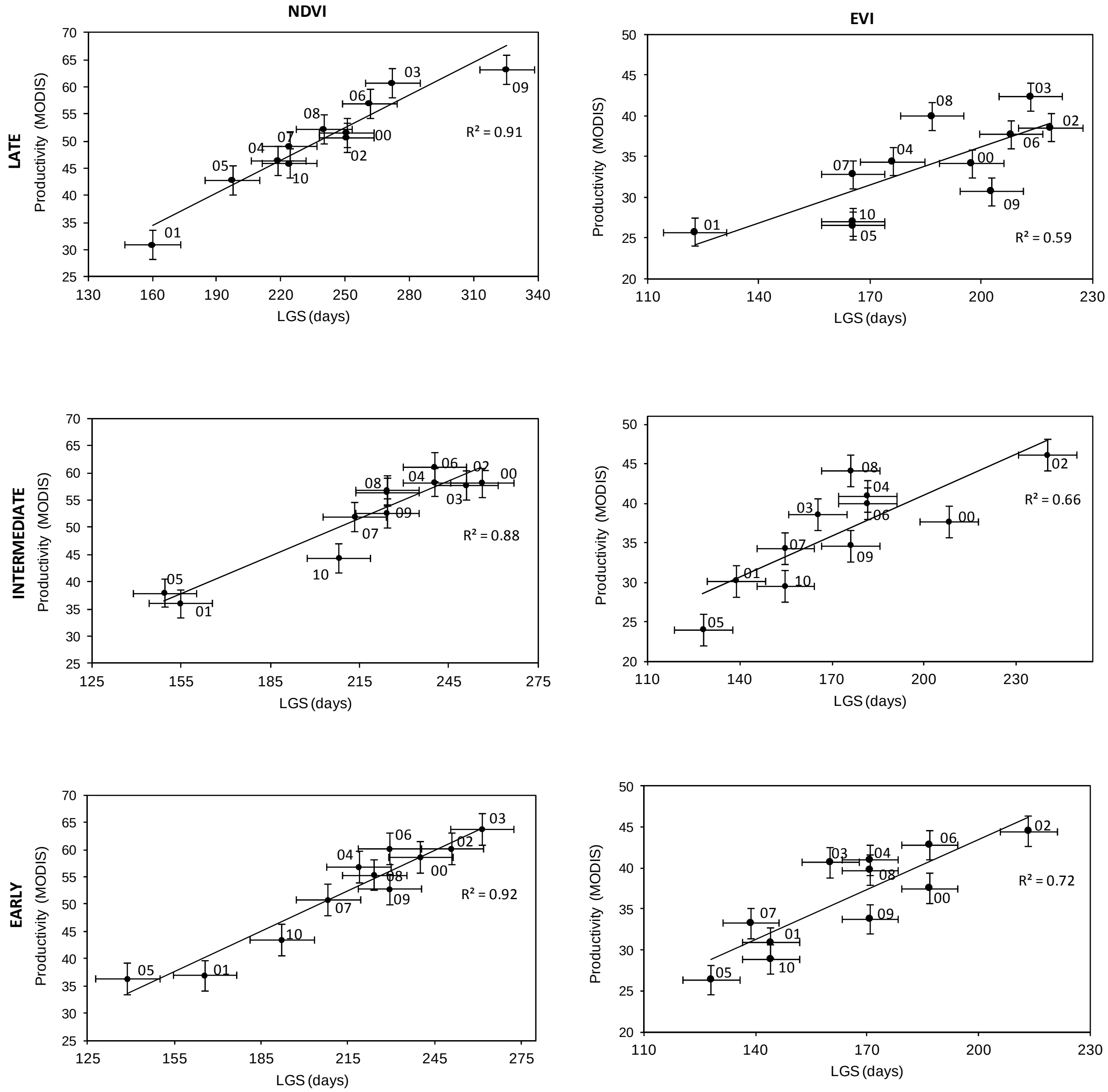


Figure 3.11 Relationship of tropical dry forest productivity from MODIS as a function of the length of the growing season at the plot level.

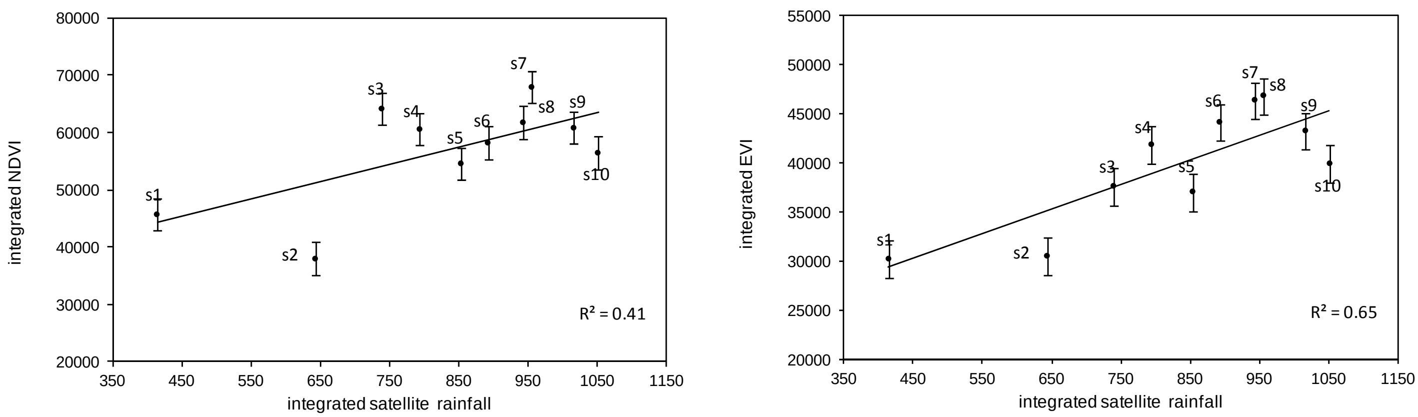


Figure 3.12 Satellite derived precipitation from the Tropical Rainfall Measuring Mission versus MODIS productivity for two vegetation indices NDVI and EVI. A stronger correlation was observed between EVI and precipitation in comparison to NDVI.

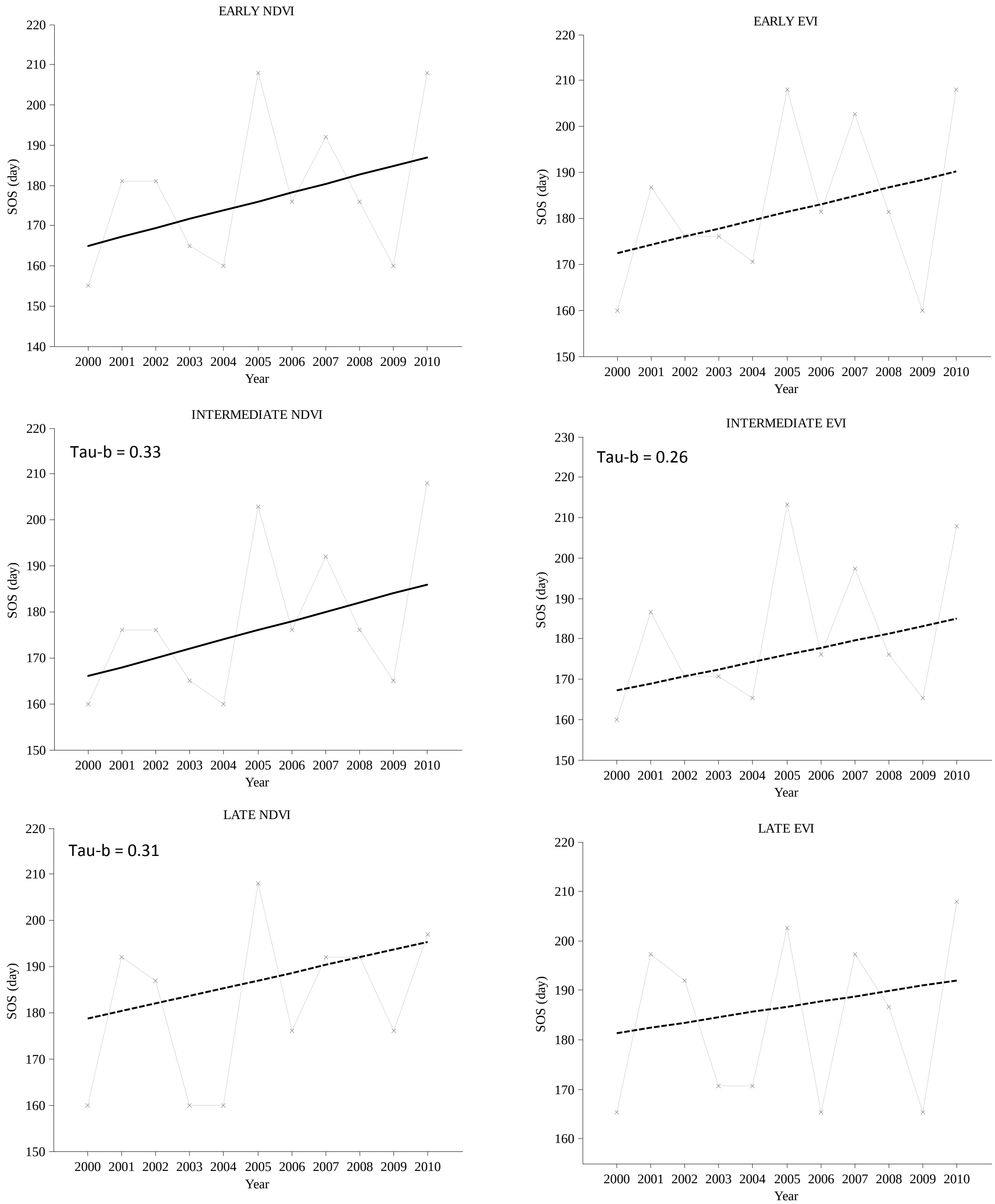


Figure 3.13 start of the growing season trend at the plot level for the NDVI (left) and EVI (right). Data is shown for each stage of succession, using a single MODIS pixel corresponding to a plot in the field.

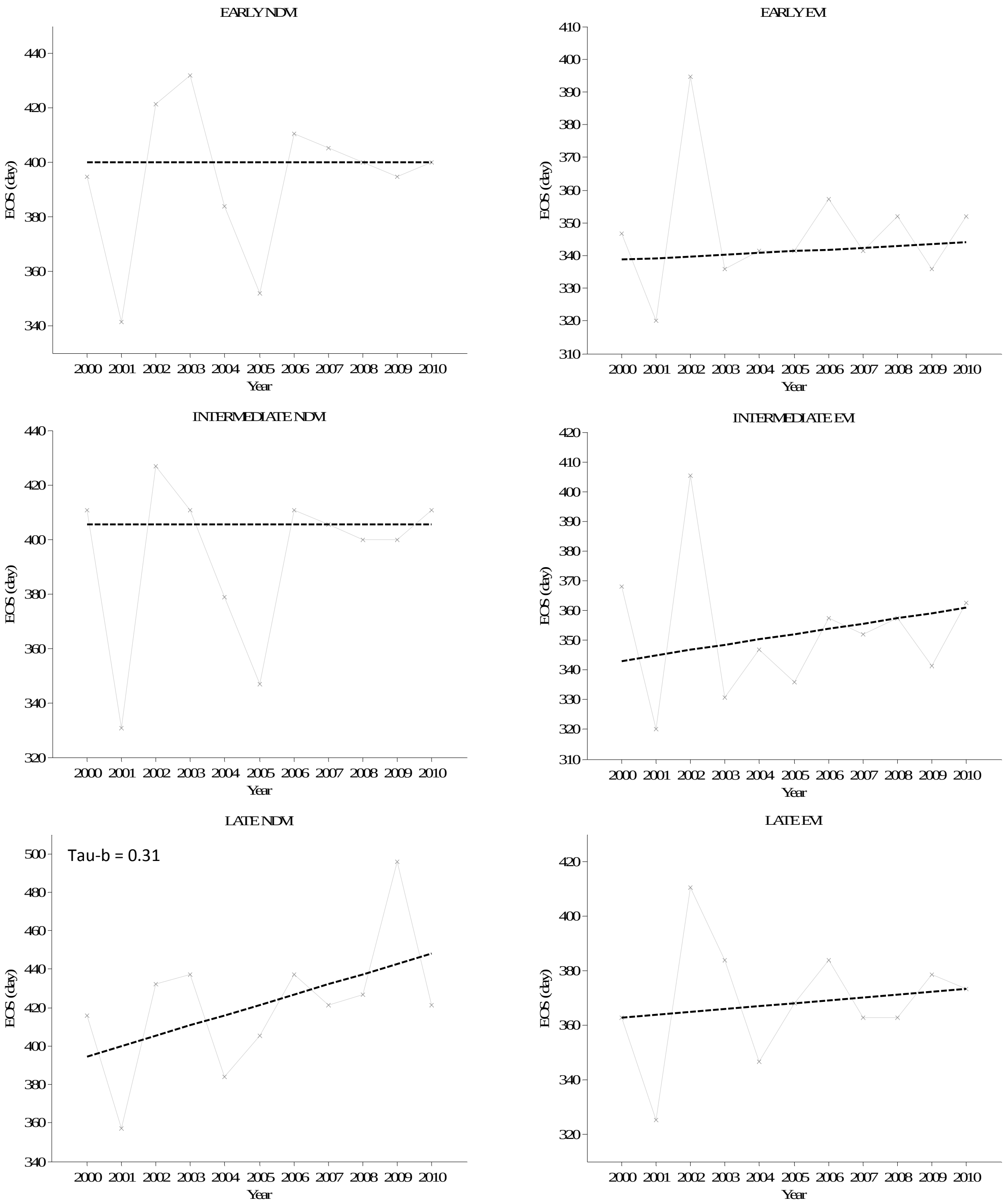


Figure 3.14 End of the growing season trend at the plot level for each stage of succession using a single MODIS pixel. The Tau rank value is shown where a trend was found (Late NDVI).

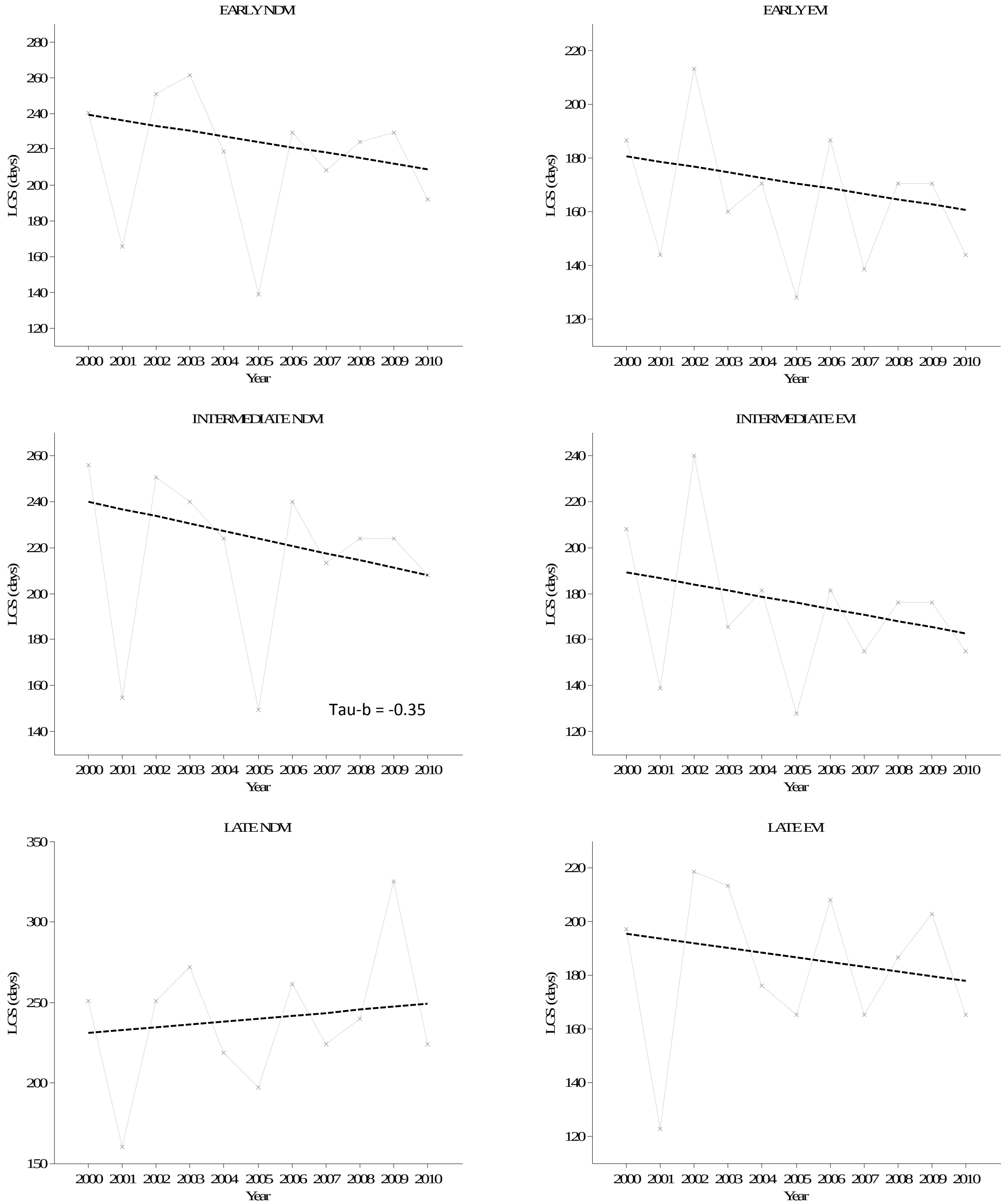


Figure 3.15 Trend analyses for the Length of the growing season at the plot level. Overall a negative slope was found for both vegetation indices with a significant trend found in the NDVI intermediate stage of succession.

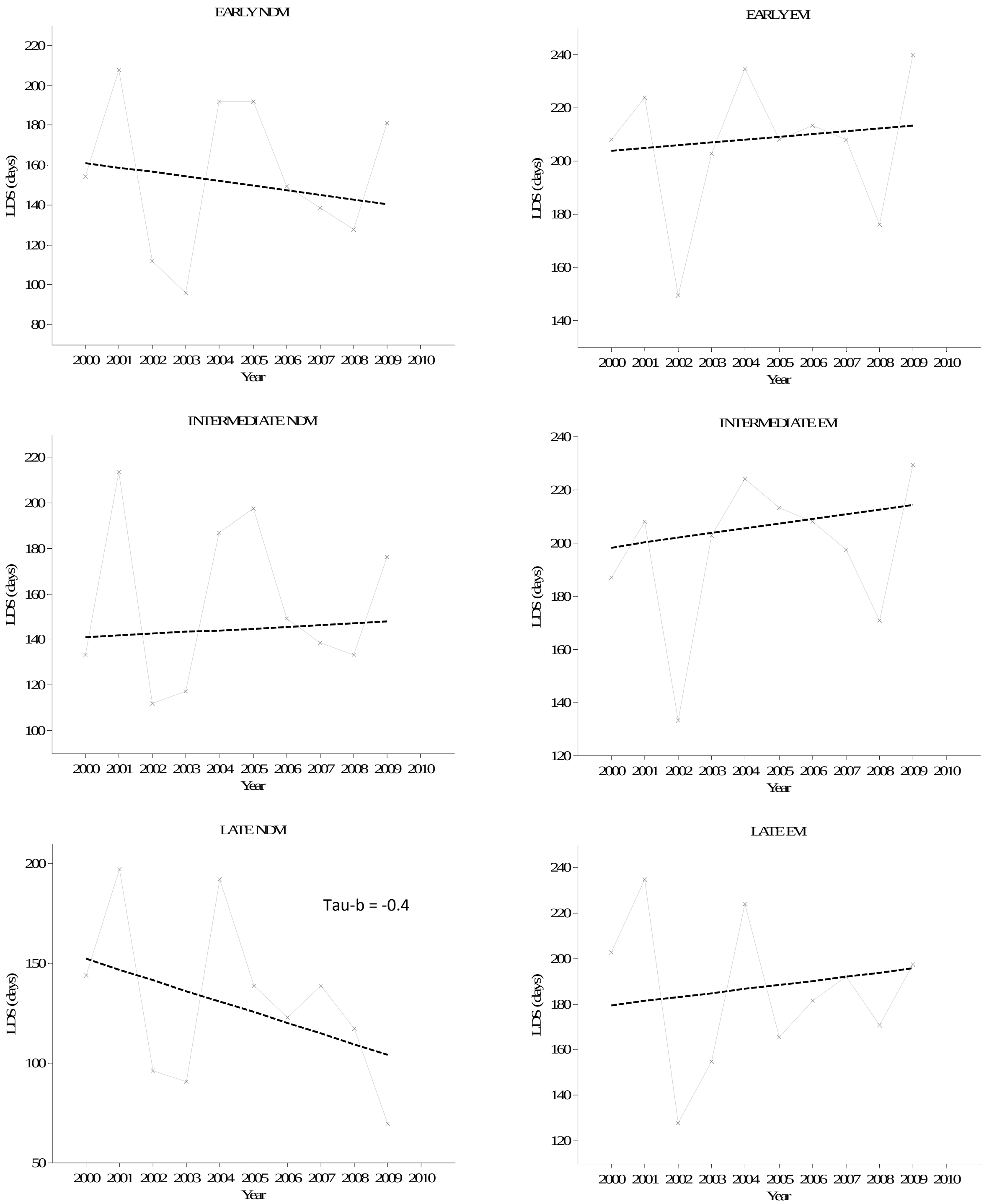


Figure 3.16 Trend analyses of the Length of the dry season at the plot level for NDVI (left) and EVI (right). A significant negative trend was observed for the late NDVI stage of succession.

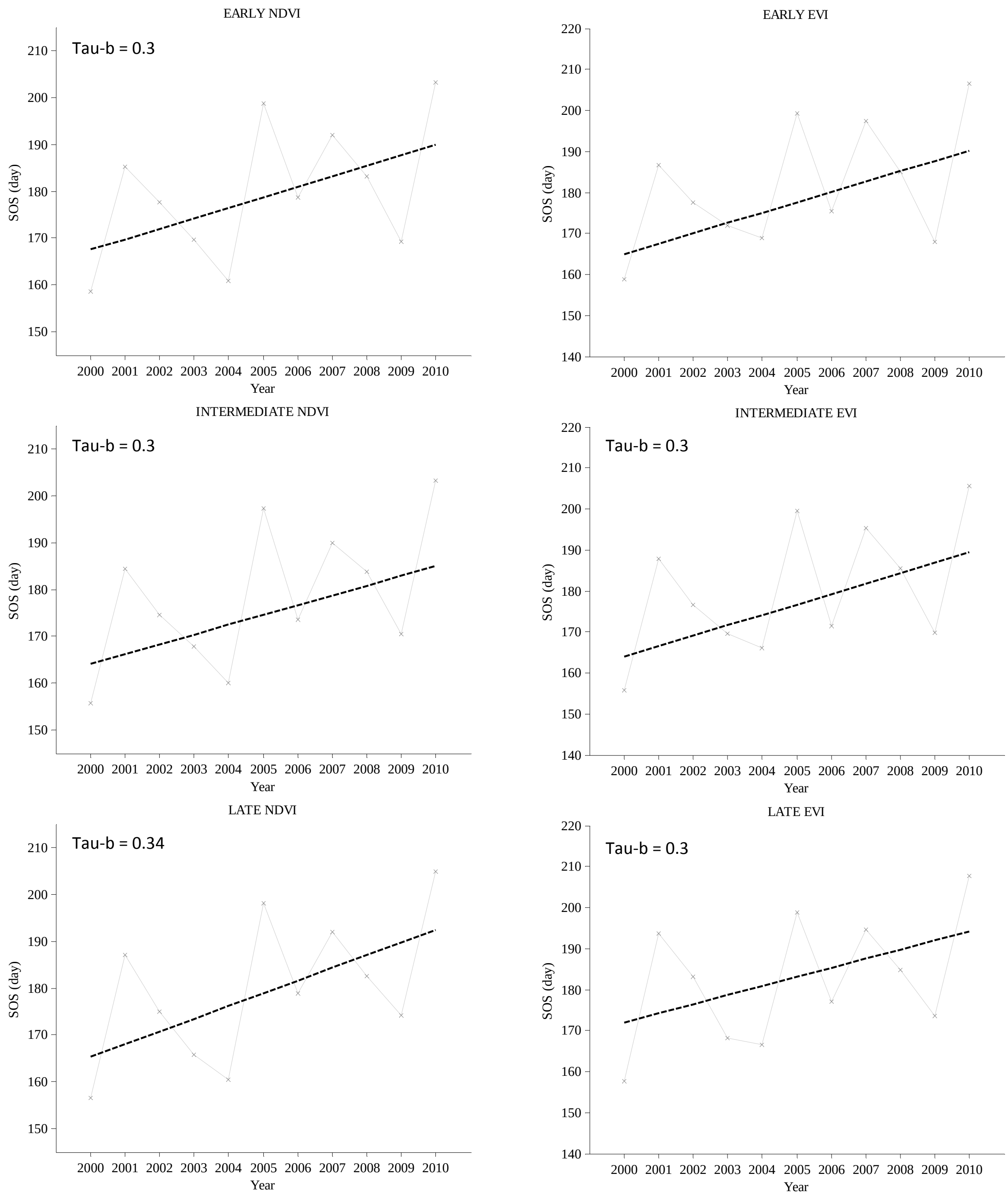
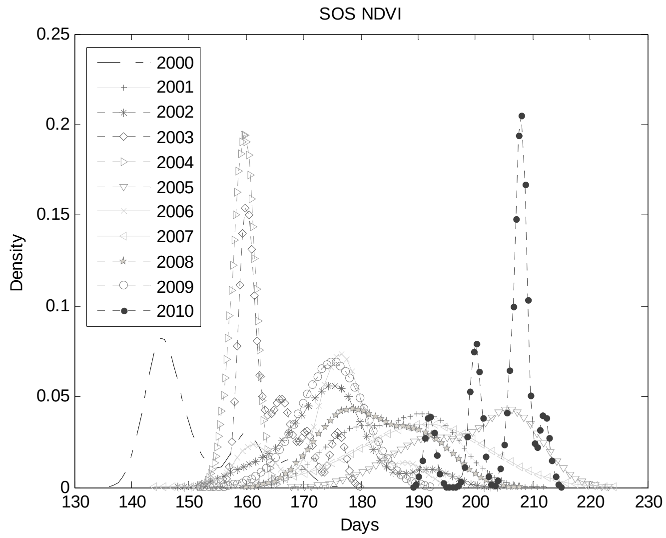


Figure 3.17 Landscape analysis of trend for the Start of the growing season. A positive trend for the start of the growing season was found across all stages of succession and for both vegetation indices (except for the EVI primary forest).



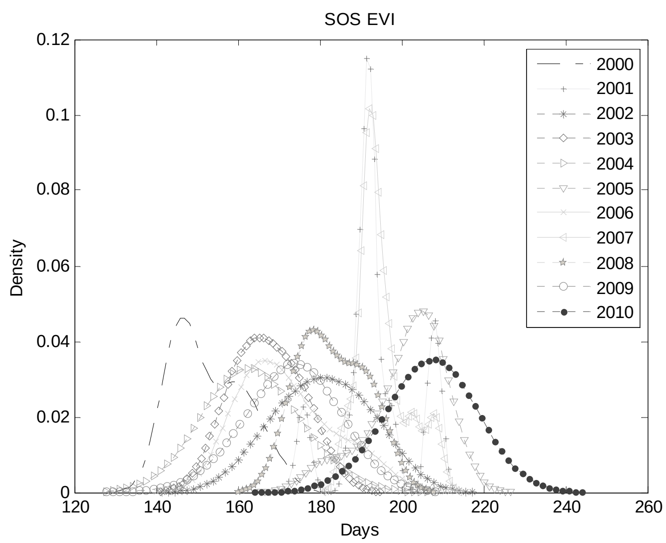


Figure 3.18 Frequency distribution of the start of the growing season. The figure shows the variability of the start of the season date over a 12 year period. Season start has been delayed over time as shown above for the year 2010 (dark line with circular markers).

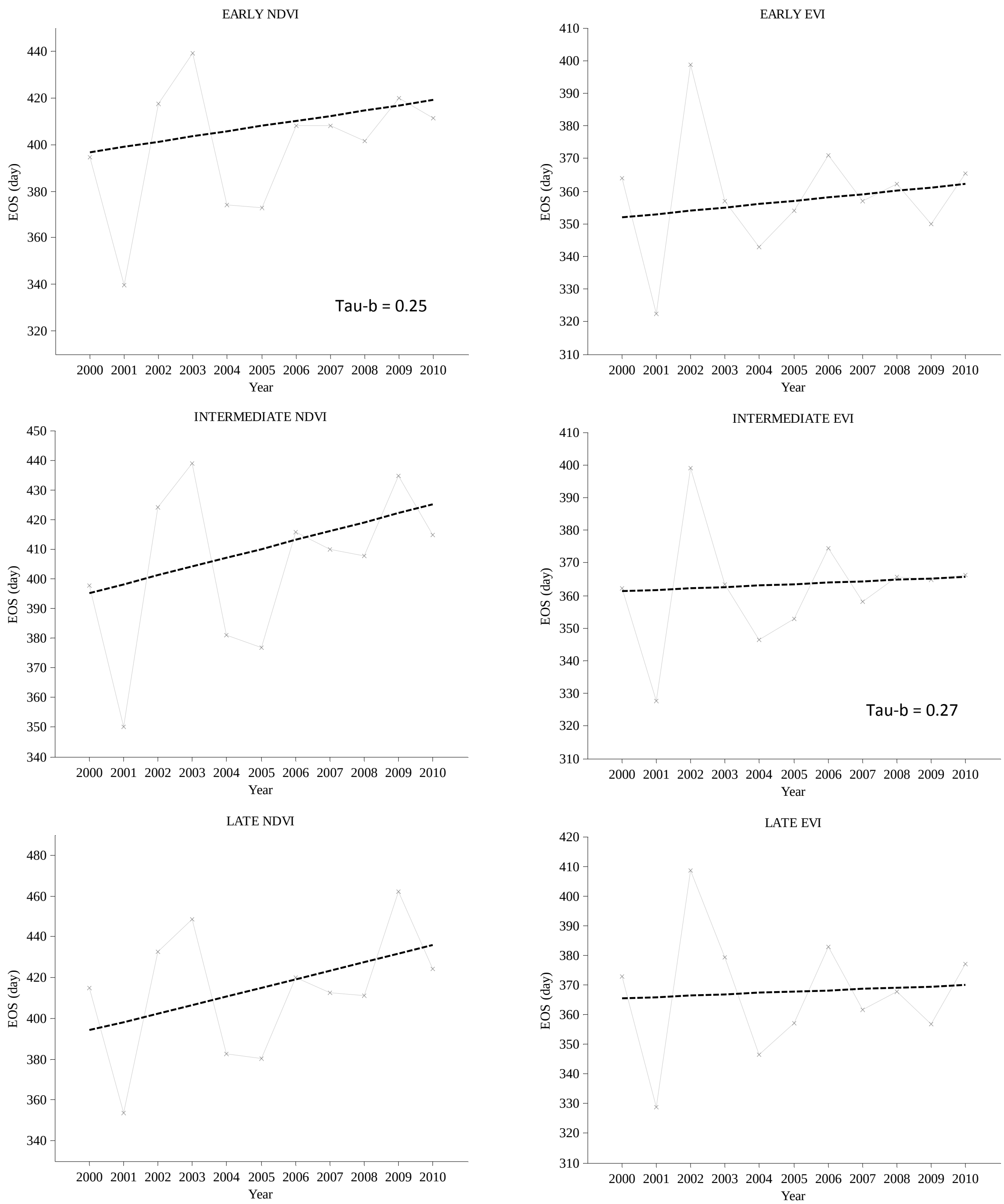


Figure 3.19 End of season trend at the landscape level. Analysis performed for NDVI (left) and EVI (right). Results show a positive trend for the early NDVI and intermediate EVI.

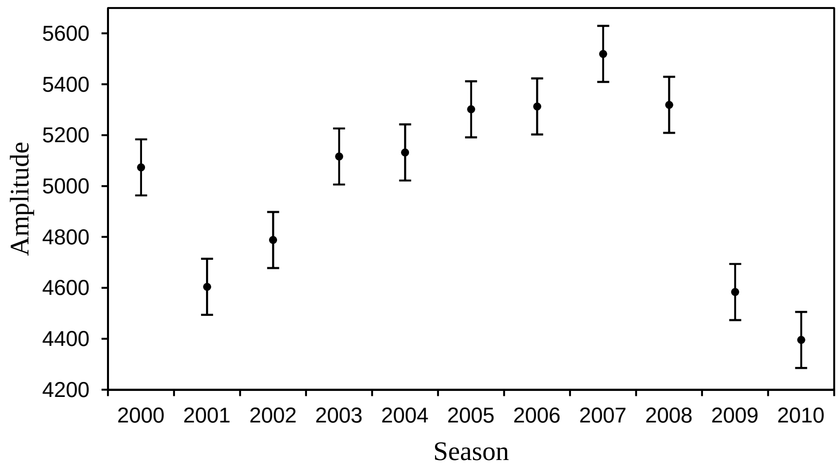


Figure 3.20 Tropical dry forest seasonal amplitude. There was a positive trend in seasonal amplitude over the past decade as observed from MODIS NDVI (Tau-b = 0.20, Significance 0.43, Z = 0.77).

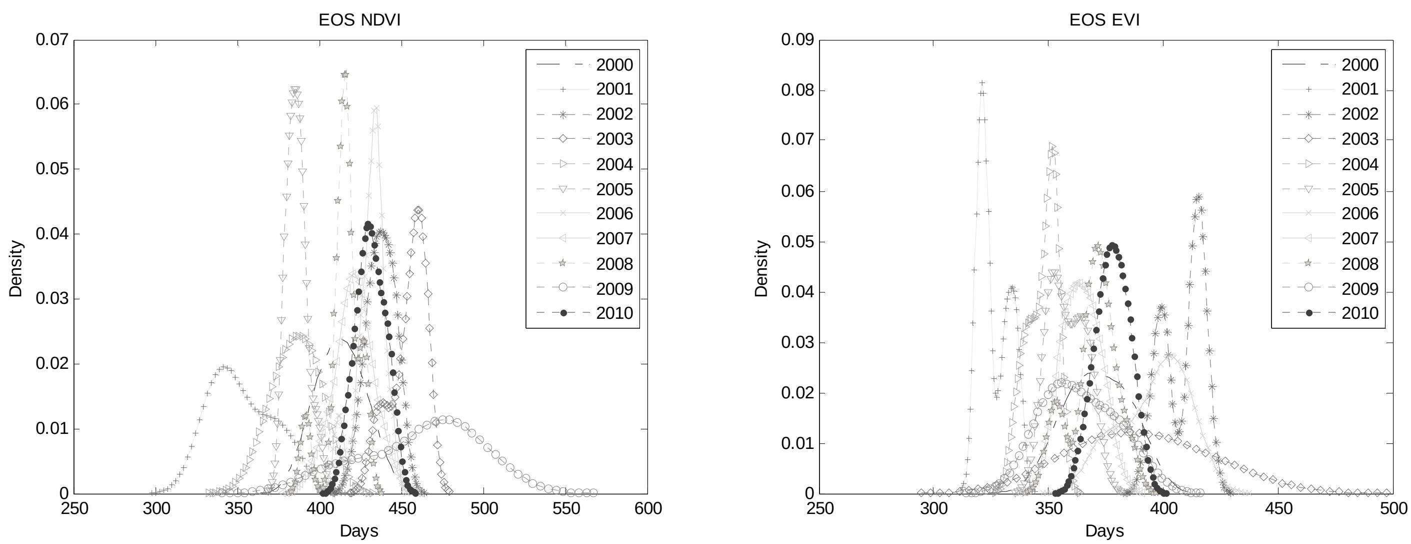


Figure 3.21 Frequency distribution of the end of the growing season. The plot above shows that 2001 was the year with the earliest end of season. The growing season ended latter during the years 2003 and 2009.

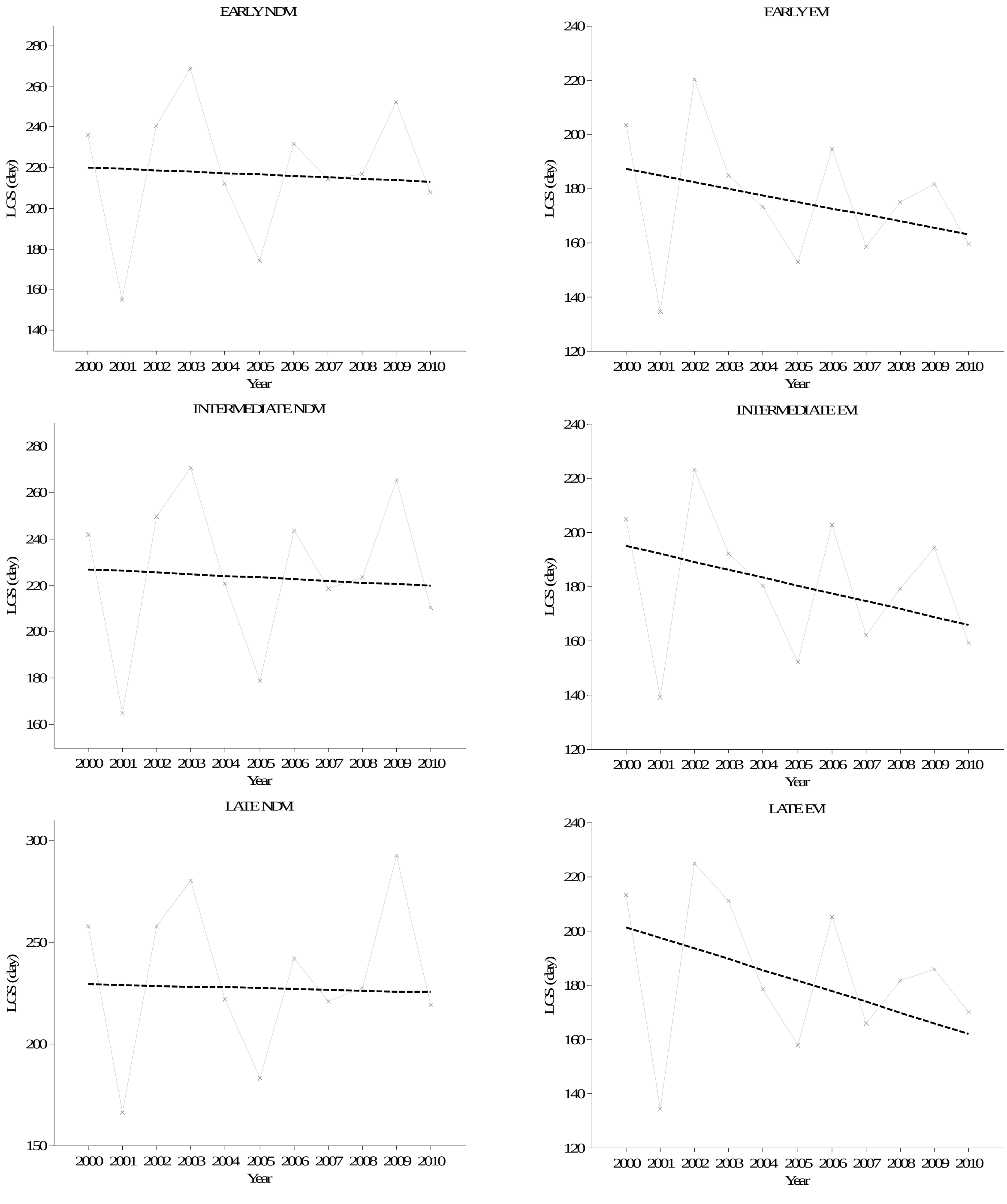


Figure 3.22 Length of growing season trend at the landscape level. No significant trend was found for the NDVI estimated length of the growing season (Z = 0). However, EVI shows a negative slope (Tau b = -0.2, Z = -0.77) for the intermediate and late stages of succession.

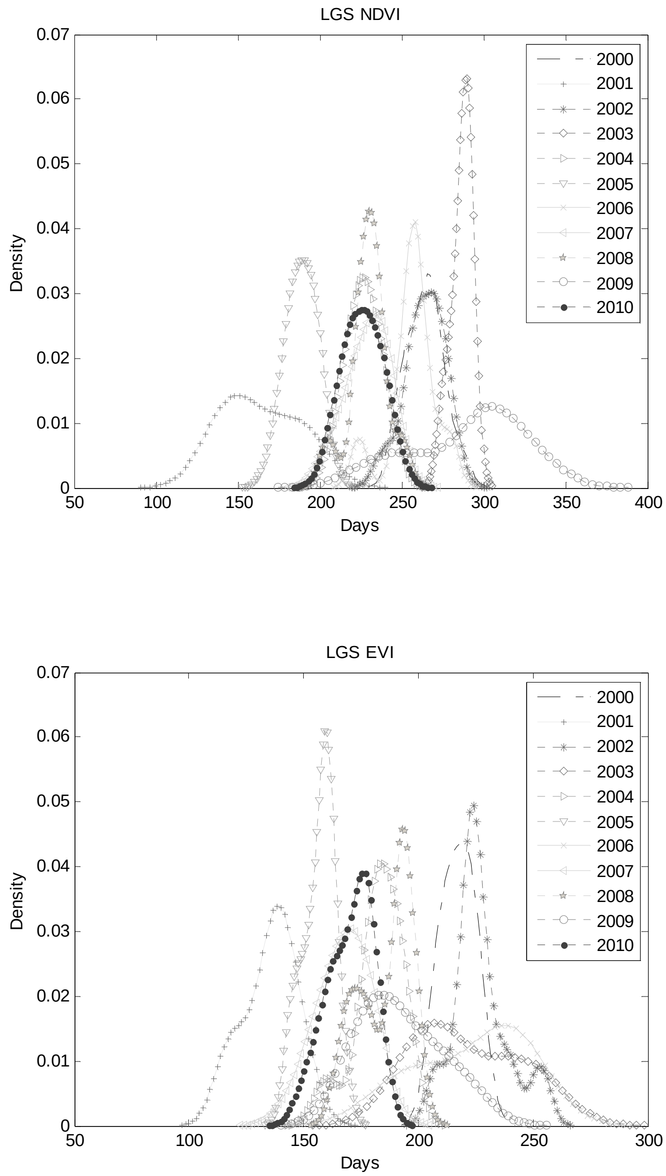


Figure 3.23 Frequency distribution of the length of the growing season. The variability for the length of the growing season was high. Both vegetation indices agreed on that the shortest season occurred during 2001.

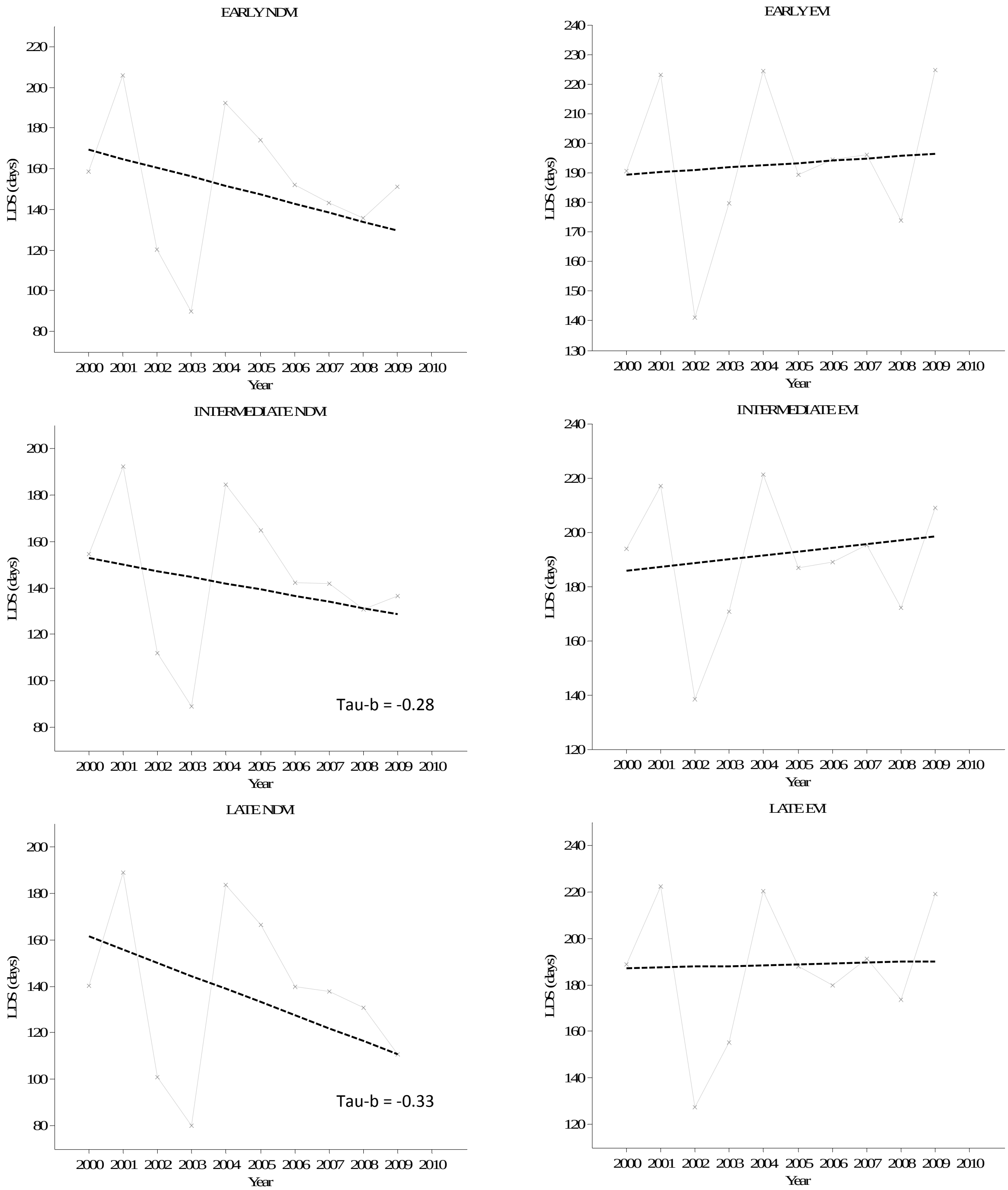
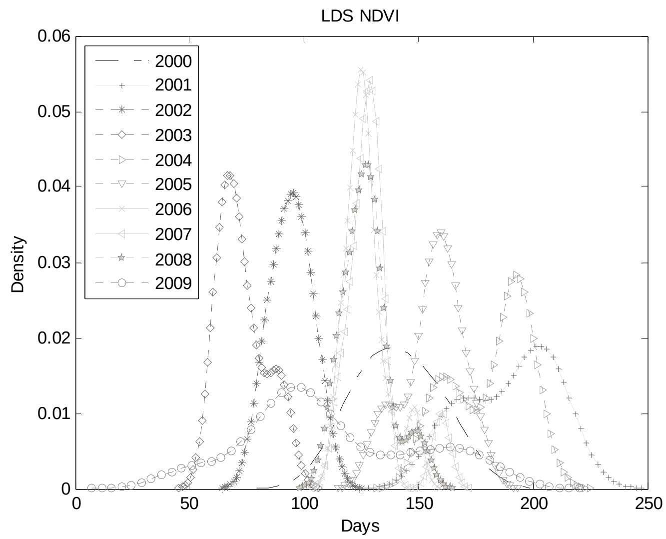


Figure 3.24 Trend analysis of the Length of the Dry Season at the landscape level. A negative slope was observed for the NDVI trend (Tau b = -0.33 for the late stage). The EVI estimates did not show a trend for the Length of the Dry Season.



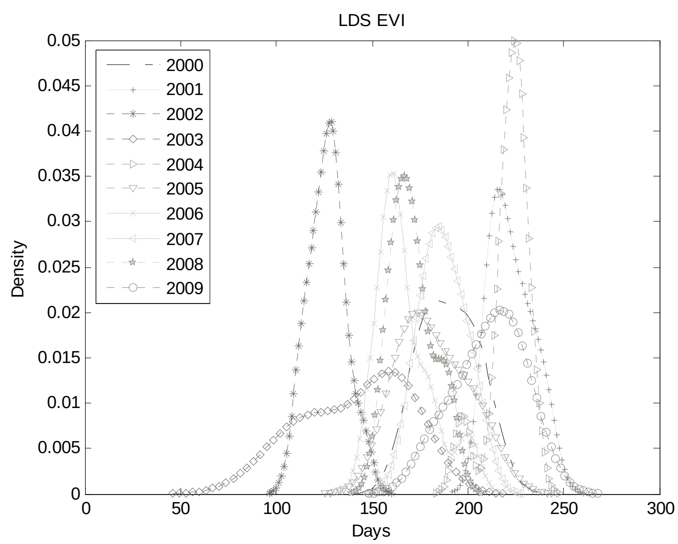


Figure 3.25 Frequency distribution of the length of the dry season. The plot above shows that the driest years for the Chamela-Cuixmala region were 2001 and 2005, where the dry season lasted from 200 to 250 days.

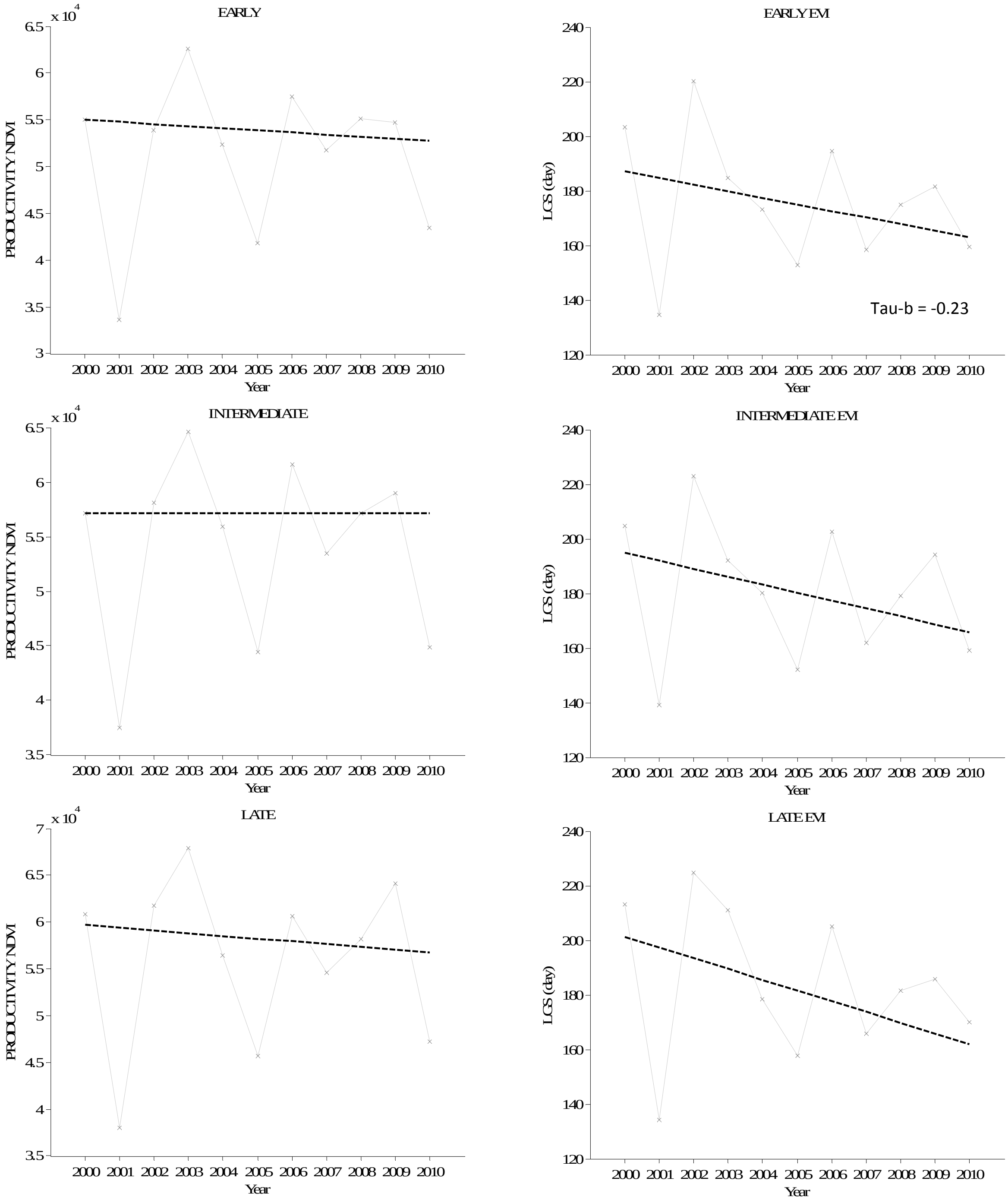
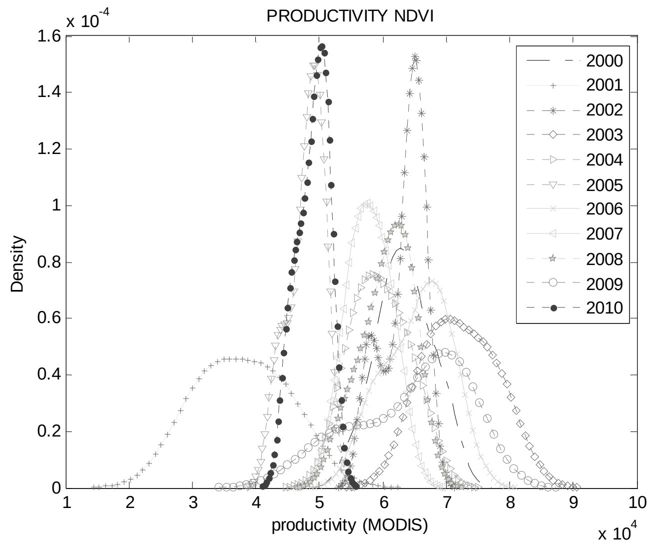


Figure 3.26 Ecosystem productivity trend at the landscape level. A negative trend in productivity (Tau b = -0.23) was found for the early EVI variable. No trends were found for the rest of successional stages and NDVI observations.



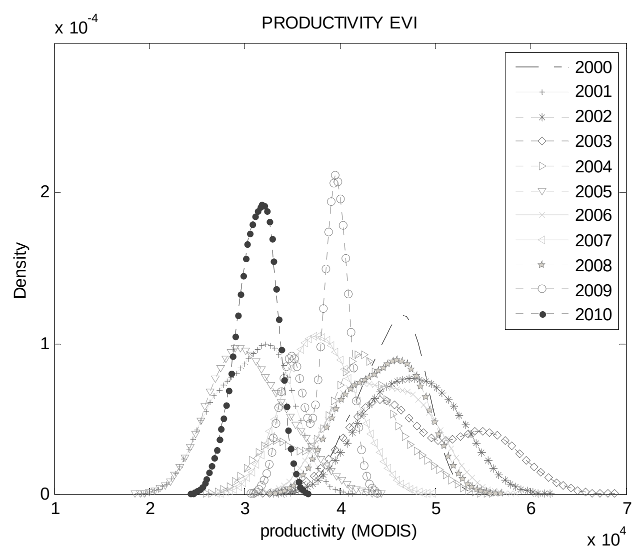


Figure 3.27 Frequency distribution of the ecosystem productivity. Tropical dry forest productivity in the Chamela region was highly variable. The NDVI quantifications showed that 2001 was the least productive year, followed by 2005. EVI shows 2005 and 2001 as the least productive years.

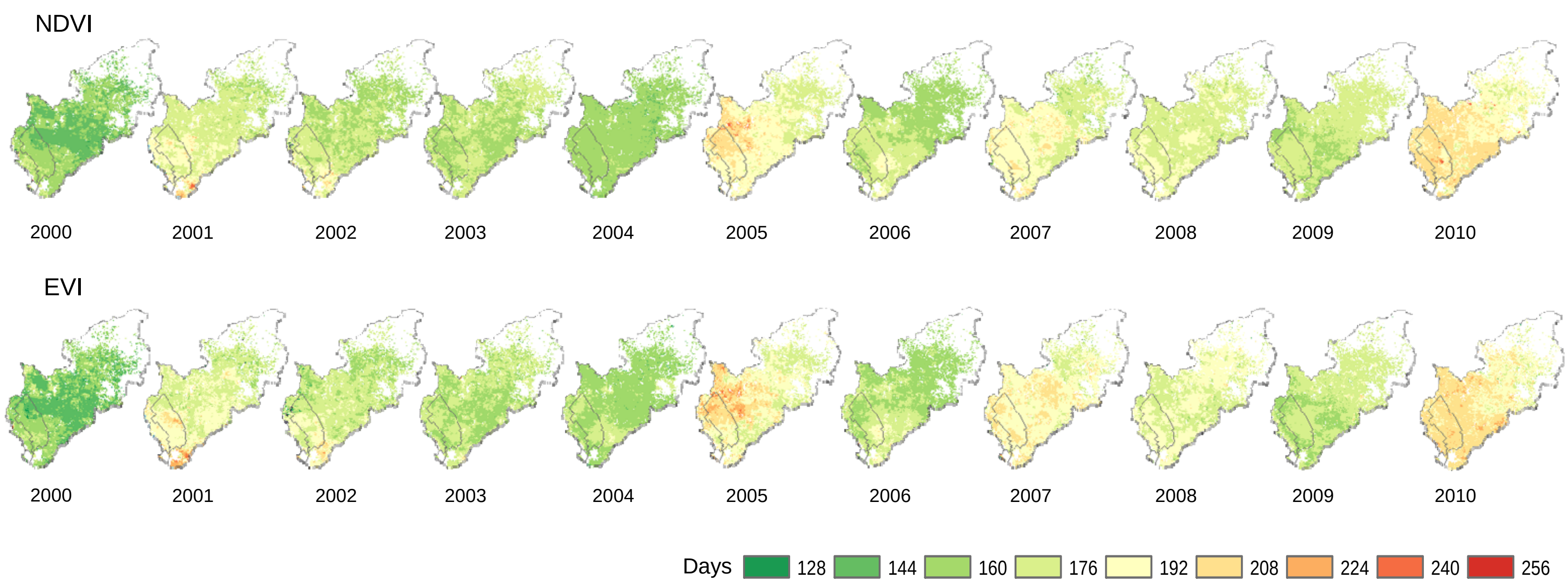


Figure 3.28 Maps of the spatial distribution of the start of the growing season as observed from NDVI (top) and EVI (bottom). Latter onset of the season occurred during the years 2001, 2005, 2007 and 2010.

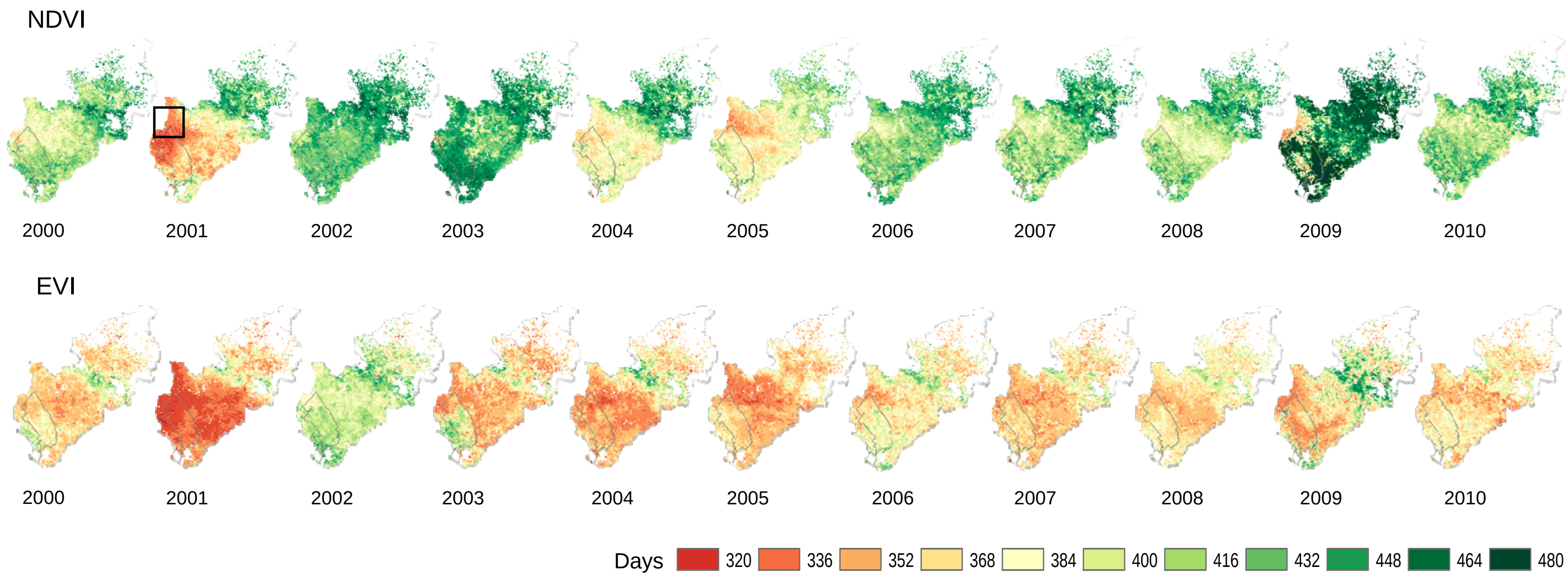


Figure 3.29 Map of the spatial distribution of the end of the growing season. The region near Ranchitos (black box) presented an extremely early end of the growing season in 2001.

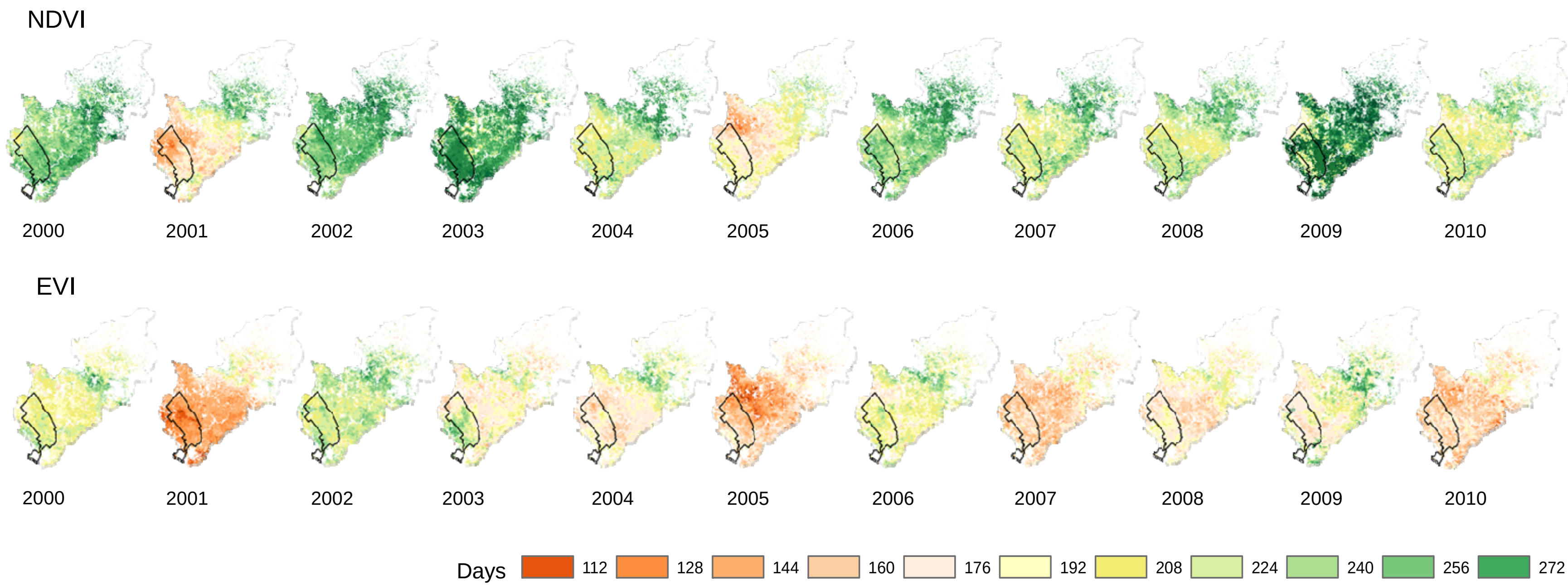


Figure 3.30 Map of the spatial distribution of the length of the growing season. Again the years 2001, 2005 and 2010 were the least productive years in the Chamela-Cuixmala region.

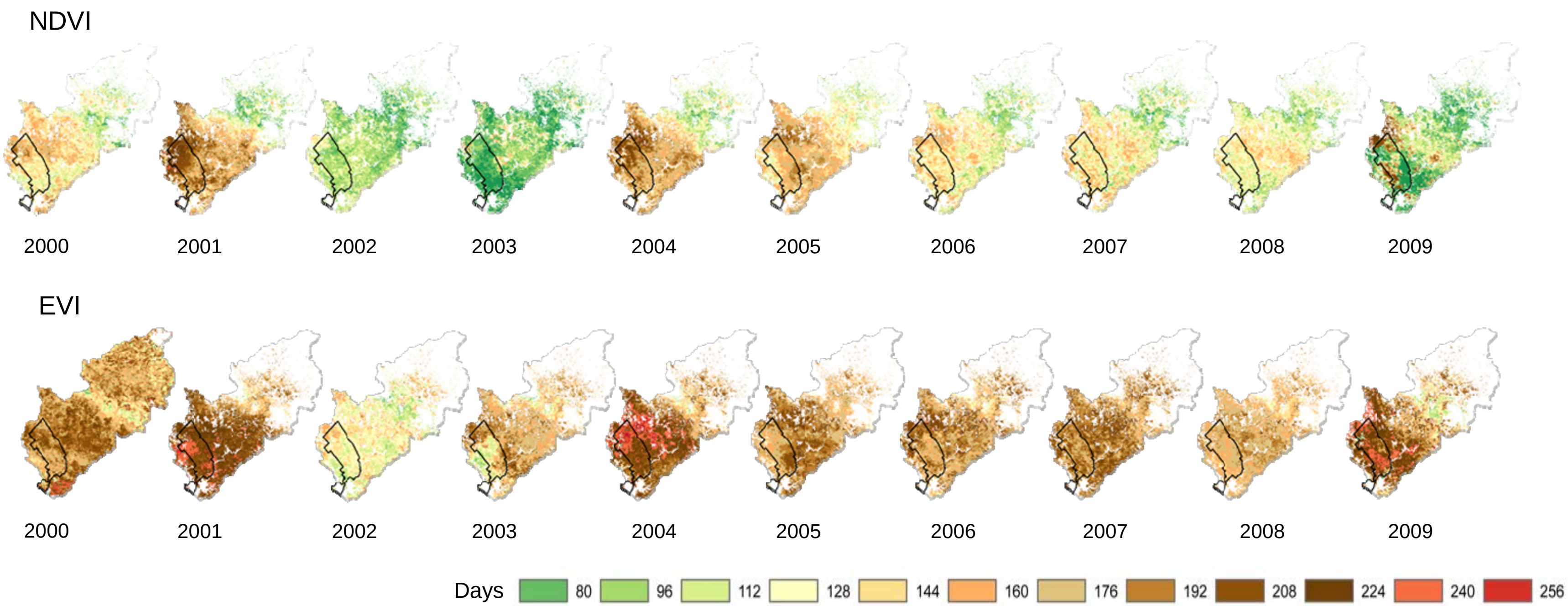


Figure 3.31 Map showing the spatial distribution of the length of the dry season. In the EVI map a long dry season was observed for the year 2004 along the Chamela basin and in the northeast of the biosphere reserve.

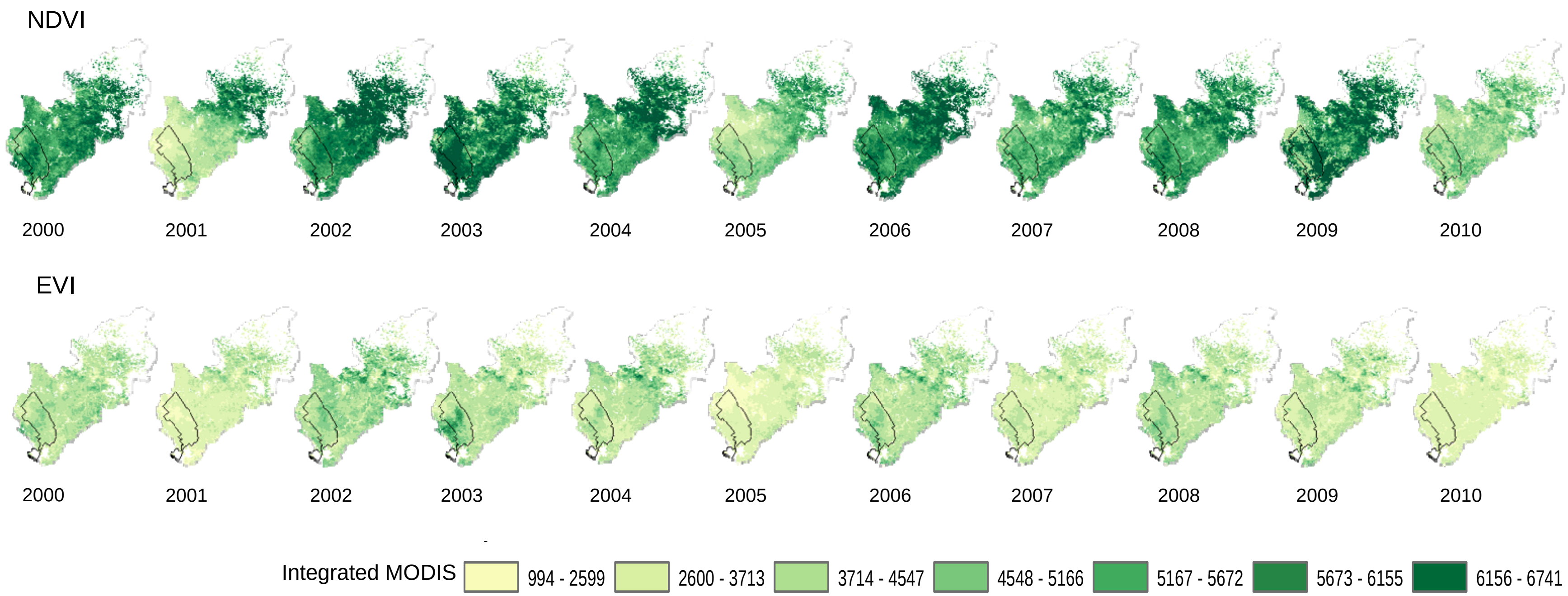


Figure 3.32 Map showing the spatial distribution of ecosystem productivity. Overall ecosystem productivity was higher in the northern region (where higher elevations occurred) the lowest productivities occurred during 2001, 2005 and 2010.

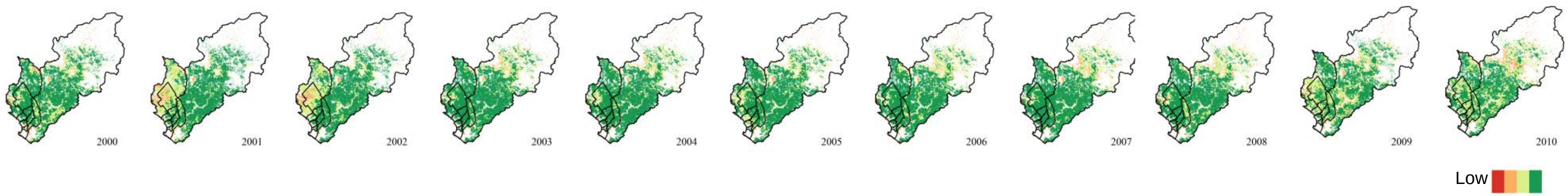


Figure 3.33 Maps of the spatial distribution of the seasonal amplitude. The map shows a decrease in ecosystem productivity for the Chamela sub-basin during 2001 and 2002.

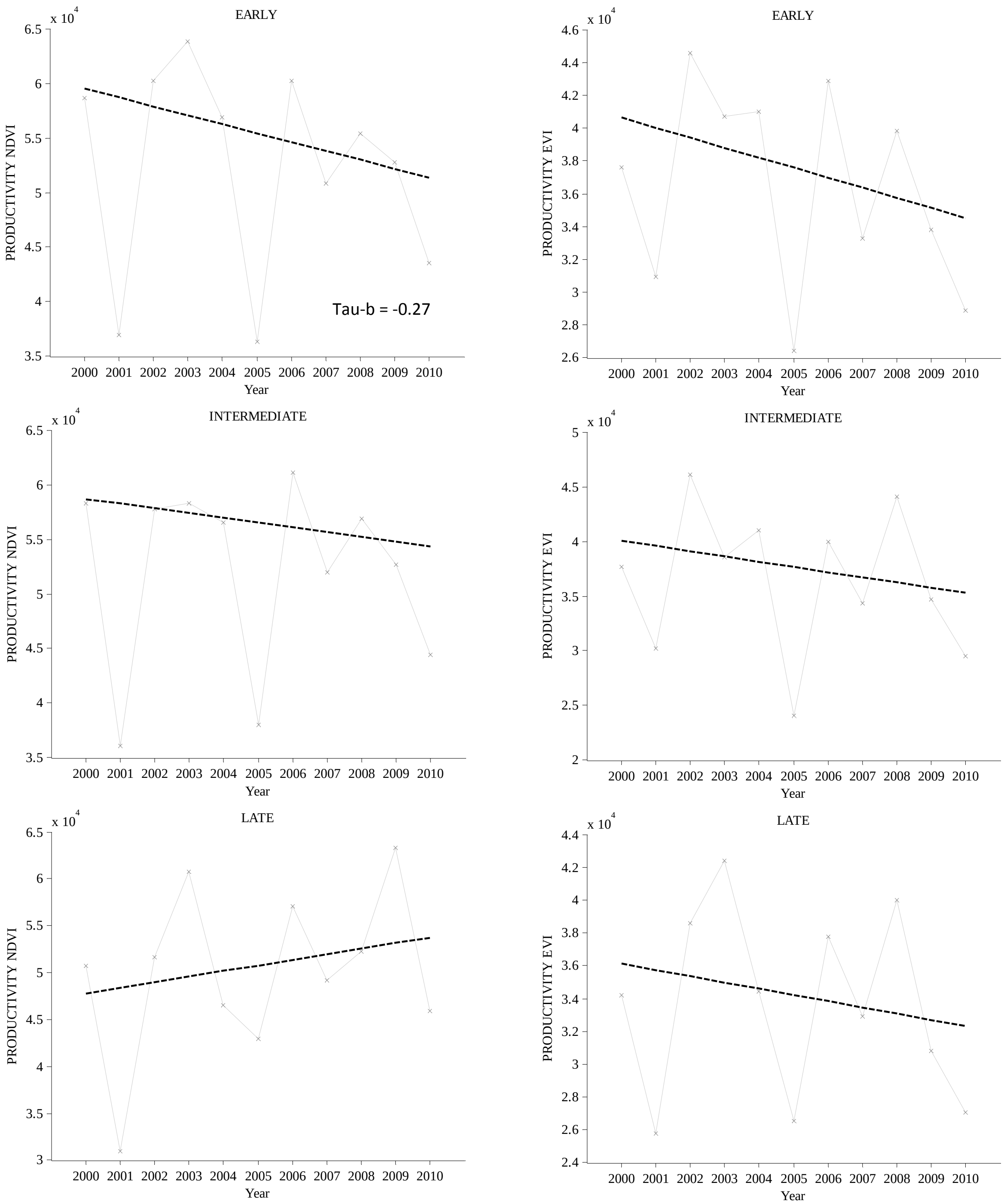


Figure 3.34Trend analysis of the Ecosystem productivity at the plot level. The graphs show the details of a single MODIS pixel for each stage of succession. A negative trend in proxy productivity was found for the early stage of succession observed by the NDVI.

TABLES

SENSOR	Spatial Resolution	Scene ID	Temporal Resolution	Year
SRTM	90m	3 N19 W106 3 N19 W105	N/A	2000
MODIS	250m	H08 V07	16 days	2000 – 2011
TRMM	4.3Km	Basin Area	Monthly Average	2000 – 2010

Table 3.1 List of satellite data used to estimate tropical dry forest seasonality, including selected products and their spatiotemporal resolution.

EARLY	Caiman			Ranchitos			Sta. Cruz		
Year	Kg	EVI	NDVI	Kg	EVI	NDVI	Kg	EVI	NDVI
2005	1077.58	33686.14	43252.24	690.59	18954.20	27899.92	1211.00	26562.43	37928.39
2006	1790.71	40109.15	57597.46	612.84	46823.92	63478.52	977.45	41667.53	59494.29
2007	2273.74	33660.11	54590.87	1040.70	32300.12	47163.27	-	33931.61	50717.81
2008	2606.65	38979.79	57437.98	1127.42	37115.59	52266.63	1661.62	43328.32	56596.28

INTERMEDIATE	Caiman			Ranchitos			Sta. Cruz		
Year	Kg	EVI	NDVI	Kg	EVI	NDVI	Kg	EVI	NDVI
2005	1171.67	26346.70	40344.93	3806.23	21616.77	34106.55	2269.45	24226.85	39575.26
2006	2672.45	37876.45	57693.93	2400.15	42534.98	63076.28	1570.09	39572.69	62586.95
2007		35390.80	52984.53		32837.88	48183.77	-	34736.07	54789.68
2008	3095.41	39574.37	51962.66	3025.62	46778.93	60322.99	2424.71	46002.65	58291.66

LATE	Gargollo			Tejon			Tejon 2		
Year	Kg	EVI	NDVI	Kg	EVI	NDVI	Kg	EVI	NDVI
2005	4121.53	26511.80	40110.38	2972.59	27052.13	44559.06	2230.63	26099.34	44175.77
2006	4830.68	40833.63	48390.87	3383.06	37701.99	62768.95	3566.64	34730.27	60041.64
2007	-	28516.05	42090.36		37384.43	55265.85	-	32769.46	50105.67
2008	3658.73	36605.59	46954.83	3262.09	44242.87	58380.13	3931.68	39155.56	51595.23

Table 3.2 Summary of satellite and field productivity estimates per year, shown for each of the three sites and per stage of succession (early, intermediate and late). Data organized per year, succession, vegetation index and weight (Kg) for nine plots.

PLOT LEVEL NDVI

SOS	3-5	10-15	50 +
tau-b	0.20	0.33	0.31
Z	0.78	1.28	1.19
EOS			
tau-b	0.01	0.03	0.31
Z	0.00	0.00	1.25
LGS			
tau-b	-0.18	-0.35	0.12
Z	-0.78	-1.42	0.47
LDS			
tau-b	-0.13	0.04	-0.40
Z	-0.44	0.08	-1.50
PROD.			
tau-b	-0.27	-0.16	0.16
Z	-1.80	-0.62	-0.62

PLOT LEVEL EVI

SOS	3-5	10-15	50 +
tau-b	0.24	0.26	0.11
Z	0.90	1.02	0.39
EOS			
tau-b	0.11	0.14	0.09
Z	0.39	0.54	0.31
LGS			
tau-b	-0.19	-0.22	-0.14
Z	-0.71	-0.86	-0.55
LDS			
tau-b	0.13	0.17	0.02
Z	0.45	0.62	0.00
PROD.			
tau-b	-0.20	-0.12	-0.09
Z	-0.77	-0.46	-0.31

LANDSCAPE LEVEL NDVI

SOS	3-5	10-15	50 +
tau-b	0.30	0.30	0.34
Z	1.24	1.24	1.40
EOS			
tau-b	0.25	0.2	0.2
Z	1.01	0.77	0.77
LGS			
tau-b	-0.01	-0.01	-0.01
Z	0	0	0
LDS			
tau-b	-0.24	-0.28	-0.33
Z	-0.89	-1.07	-1.25
PROD.			
tau-b	-0.05	-0.01	-0.05
Z	-0.15	0	-0.15

LANDSCAPE LEVEL EVI

SOS	3-5	10-15	50 +
tau-b	0.23	0.3	0.3
Z	0.93	1.24	1.24
EOS			
tau-b	0.07	0.27	0.01
Z	0.23	1.08	0
LGS			
tau-b	-0.16	-0.2	-0.2
Z	-0.62	-0.77	-0.77
LDS			
tau-b	0.2	0.11	0.02
Z	0.71	0.35	0
PROD.			
tau-b	-0.23	-0.2	-0.2
Z	-0.93	-0.77	-0.77

Table 3.3 - Kendall non parametric test summary. Results are organized by tropical dry forest successional stage at two levels of analysis, plot and landscape. The measure was implemented for two vegetation indices (NDVI and EVI). Significant observations are highlighted in orange.

CHAPTER 4. CONCLUSIONS

Tropical dry forests are the most endangered ecosystems in the tropics (Janzen, 1988b), although millions of people depend from them worldwide (Maass et al., 2005). More than 97% of the remaining tropical dry forests in the world are still threatened by several reasons, including fragmentation, land use practices and climate change (Miles et al., 2006). Over the past decade, systematic efforts have accurately represented the scope and conservation status of Neotropical dry forests (Portillo-Quintero and Sanchez-Azofeifa, 2010; Quesada et al., 2009; Sanchez-Azofeifa et al., 2005b).

The response of tropical dry forest to climate change has been described at large scales (Galvao et al., 2011). However, ecosystem functioning at the landscape level needs to be urgently investigated in order to understand the processes occurring between plant communities at different stages of succession. For instance secondary forests are crucial to tropical dry forests continuous development (Quesada et al., 2009). A conundrum for such characteristic existed in old ways of thinking conservation, where efforts have been intensively placed in large fragments of mature dry forest only, representing enclosed units of management. As a consequence less than 0.1% of the remaining tropical dry forest in Mesoamerica were considered worthy for conservation (Janzen, 1988a).

This thesis addressed essential knowledge gaps in tropical dry forests monitoring and environmental processes at the regional level, using state of the art remote sensing techniques through the following chapters.

Chapter two: *Land cover assessment of the Chamela-Cuixmala region*

The need for a thematic map depicting the land cover status of the Chamela-Cuixmala region has been clearly indicated by the Tropi-Dry research network, based on the analysis performed in a wide range of disciplines including remote sensing and human geography (Sanchez-Azofeifa et al., 2005a). The application of machine learning classification to estimate tropical dry forest has been successful at 500 meters resolution (Portillo-Quintero and Sanchez-Azofeifa, 2010). Our analysis takes the method also to evaluate tropical dry forest distribution at 15 meter resolution, including additional parameters to improve dry forest discrimination and successional stages. The overall map accuracy was 92 percent, also improving previous maps of tropical dry forest extent. The tropical dry forest map shows that the biosphere reserve and its surrounding areas have the best preserved forest. However, potential threats still remain located northwest and southeast of the reserve near agricultural fields. We expect that this research can benefit the scientific community and society in two main components. First, as a general procedure for tropical dry forest mapping. Second, that results from this study can be used to support land cover conservation and adequate resources management in the Chamela region, currently facing urban development and road modernization.

Chapter three: *Modeling Tropical Dry Forest Phenology*

Tropical dry forest faces changes in precipitation patterns and temperature over the next two decades (Magana et al., 1997). This research linked results from a detailed land cover analysis with satellite time series to monitor the effects of climate change in the Chamela-Cuixmala region, also describing dry forest phenology at three levels of succession. MODIS data combined with climatic data provides a tool to monitor the seasonal development of Tropical dry forest. TIMESAT offered a robust method to determine the dates of seasonal parameters such as the length of the growing seasons via satellite time series. Positive trends were found for the start and end of the growing seasons in the late stage of succession. Observed shifts on greenup and senescence did not show a significant effect in ecosystem productivity. However, regional phenology distribution showed the lowest estimations of productivity near perturbed areas and primary dry forest. The length of the growing season was closely related to ecosystem productivity, but no significant trends were observed in the season length or productivity during the past decade, except for the EVI early stage of succession which showed a negative trend. Tropical dry forest responds strongly to precipitation and seasonal amplitude, producing strong variations in seasonality. Nevertheless tropical dry forest phenology can be accurately estimated via satellite time series. Further research needs ecosystem productivity models to have a better understanding of the relationship of tropical dry forest phenology and land processes occurring in the region.

OVERALL SIGNIFICANCE

This thesis presents an improved land cover characterization of the Chamela-Cuixmala region. We have also shown an application to discuss ecosystem processes and their relationship with tropical dry forest phenology. Continuous monitoring of key ecosystem parameters will provide new possibilities to study the response of tropical dry forest to climate change, allowing the creation of future scenarios for tropical dry forests development.

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