A FOREST OPTIMIZATION MODEL TO REDUCE THE RISK OF HURRICANE DAMAGE IN EASTERN NICARAGUA

by

Fernando Jose Mendoza Jara

APPROVED BY SUPERVISORY COMMITTEE:

___

Denis J. Dean, Co-Chair

___

Michael Tiefelsdorf, Co-Chair

___

Ronald Briggs

___

Fang Qiu

To my family and friends for their strength and encouragement.

A FOREST OPTIMIZATION MODEL TO REDUCE THE RISK OF HURRICANE DAMAGE IN EASTERN NICARAGUA

by

FERNANDO JOSE MENDOZA JARA, MS

DISSERTATION

Presented to the Faculty of

The University of Texas at Dallas

in Partial Fulfillment

of the Requirements

for the Degree of

DOCTOR OF PHILOSOPHY IN

GEOSPATIAL INFORMATION SCIENCES

THE UNIVERSITY OF TEXAS AT DALLAS

May 2015

ACKNOWLEDGMENTS

I owe a special debt of gratitude to my advisors Dr. Denis Dean and Dr. Michael Tiefelsdorf. They supported my studies with not only being patient and providing guidance, but also by sharing their experience and knowledge in forestry, spatial optimization, and statistics to complete my dissertation. In addition, I would express thanks to the committee members, Dr. Ronald Briggs and Dr. Fang Qiu, for their invaluable suggestions during the progress of this dissertation. The author appreciates the help of Dr. Kerry Emanuel, professor of Atmospheric Sciences of MIT, for providing his relevant data-model to simulate synthetic hurricanes. Finally, I am indebted to the Organization of American States (OAS) for sponsoring my PhD education at UTD and the Innovative Application of ICTs in addressing Water-related Impacts of Climate Change project (ICTWCC) for funding this dissertation. Additionally, the ICTWCC project strengthened my capacities in investigative methods and recognized this study in the field of Climate Change.

November 2014

A FOREST OPTIMIZATION MODEL TO REDUCE THE RISK

OF HURRICANE DAMAGE IN EASTERN NICARAGUA

Publication No. ___________________

Fernando Jose Mendoza Jara, PhD
The University of Texas at Dallas, 2015

Supervising Professors: Denis J. Dean, Co-Chair
Michael Tiefelsdorf, Co-Chair

Can we successfully propose a forest management plan to reduce the risks of impacts from hurricanes by using historic data of damage caused by hurricanes in the past? Due to their geographical locations and poverty status, Central American countries are vulnerable to extreme meteorological phenomena. This research is located in eastern Nicaragua, specifically located in the Autonomous Region of the Northern Atlantic (RAAN). Nicaragua is the third most highly impacted country in the world by the passage of tropical storms. Moreover, it occupies third place in a ranking of countries most affected by long-term climate risk index (Harmeling and Eckstein 2012). After Hurricane Felix (2007) hit eastern Nicaragua, the potential environmental problems (e.g., forest destruction and flooding) associated with hurricanes became evident. Felix destroyed 1.2 million of hectares of dense and open broadleaf, forest fallow, and pine forests. As a result, this research addresses an important question: what land management strategies (forestry activities and land uses) will be most effective in decreasing hurricane damage? First, this study predicts damage rate related to synthetic hurricanes in four land use classes. The prediction model is based upon Data Model Calibration (DMC) based on observed forest damage from Hurricane Felix (2007). Then, it develops a Forest Optimization Model (FOM) that produces a land management plan which minimizes damages risks posed by hurricanes. In addition, this investigation determines which forestry management activities can best be assigned to a series of spatially predefined management areas (land management allocation solution). The findings of this study suggest that wind speed, distance from the path, elevation, and slope can be employed as explanatory variables to measure potential damage from hurricanes. The results of the sensitivity analysis of the FOM demonstrate that feasible solutions are strongly regulated by the interaction of four factors: (1) the feasible area assigned to each landuse, (2) the minimum and maximum area constraints for each landuse, (3) landuse implementation costs, and (4) the available budget.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

1.1 Introduction

Due to their geographical location (i.e. with oceans at either side) and their high levels of poverty, Central American countries are particularly vulnerable to violent natural phenomena. Nicaragua is a country highly vulnerable to earthquakes, volcanic eruptions, floods, landslides, hurricanes, droughts, and tsunamis (the last time Nicaragua was hit by a tsunami was on September 2, 1992). The population at risk to hurricanes and tropical storms in Nicaragua is 1.3 million, the equivalent of 25.4% of the country's total population (Ministerio del Ambiente y los Recursos Naturales 2008). Moreover, Nicaragua is the third most highly impacted country in the world by the passage of tropical storms and it occupies the third place in a ranking of countries most affected by extreme weather events, according to Germanwatch (the first and second places are held by Honduras and Myanmar for a period of 20 year – 1992-2011, respectively). These meteorological catastrophes are mainly hurricanes, flooding, regional droughts and landslides (Harmeling and Eckstein 2012).

Moreover, according to the Center of Climate and Energy Solutions (2011) and Knutson et al. (2007, 1549 - 1565), the North Atlantic has experienced a clear increase in the frequency of tropical storms and major hurricanes within the past two or three decades. This increase in frequency correlates strongly with rise in North Atlantic sea surface temperature. Recent peer-reviewed studies (Emanuel 2005, 686-688) link this temperature increase to global warming. It is probable that coastal areas along the Atlantic can expect higher risk of hurricanes over the next 40 years, whether from natural cycles, effects of climate change, or both (Knutson et al. 2007, 1549 - 1565). The increase of the number of tropical cyclones, duration, and frequency (Webster et al. 2005, 1844-1846) results in adverse consequences to those areas exposed to the Atlantic basin. Forest damage and flooding are part of those consequences. The relevant question becomes “How can we spatially analyze those negative impacts in a large area?”

“Theory development and model formulation” and “Watershed Approach” were two of three emerging topics identified by earlier geographers (Young et al. 2004, 17-77). Watershed research has emphasized the effects of landuse and land-cover change on run-off, sedimentation, stream habitat, and water supply. Watersheds continue to be a strong focus of geographic research because they link physical and ecological concerns (Browner 2010). Nowadays, in Nicaragua, several Natural Resources management projects are adopting a watershed approach because it allows for the study of similar conditions based upon drainage. Specifically, FOCUENCAS (*Fortalicemiento de la Capacidad Local para el Manejo de Cuencas y la Prevencion de Desastres Naturales*) is a watershed approach project in Nicaragua that works by strengthening the local capacity in watershed management and prevention of natural disasters. Another outstanding example is “*La Red Nacional de Organizaciones de Cuencas – RENOC*,” which aims to contribute to processes involving the protection, restoration and sustainable use of river basins of Nicaragua, promoting the exchange, the incidence, and the strengthening of institutions involved in the watershed management. Watershed land management in eastern Nicaragua represents a complex process due to the increased number of hurricanes in the Atlantic basin. Understanding the adverse influence of such hurricanes requires an integrated approach that adopts land management changes in the view of future hurricanes. To obtain meaningful predictions from an optimized land management model, the linkage between how hurricanes could behave and current land management activities is essential.

1.2 Problem Statement

Hurricanes pose many potential environmental (e.g., forest destruction and flooding) and social (e.g., village destruction and death) impacts on the regions of landfall and along their inland path. A prominent example was Hurricane Felix, which destroyed more than a million of hectares of forest and dismantled hospital facilities, houses and roads in the Autonomous Region of the Northern Atlantic (RAAN) and Autonomous Region of the Southern Atlantic (RAAS) regions, in 2007 (for example the communities of Kukrira, Bismuna, Pahra, Tuapi, and Barra de Sandy Bay, which suffered severe damage). This destruction had serious ecological impacts in terms of carbon dioxide emission, incidents of wild fire, loss of forestry habitat, and loss of timber (Figure 1.1). Hurricane Felix was estimated to destroy a total of 5 million cubic meters of timber in the areas of heavy damage (Figure 1.2) (ACAN-EFE 2007; Aguirre and Salinas-Maldonado 2007).

Past research has widely acknowledged that land management could support the reduction of forest damages and flooding risks. Based on damages of historic hurricanes (Figure 1.1) and modeled synthetic hurricanes (section 3.2), can we successfully propose a forest management plan in order to reduce the risks of impacts from hurricanes? Studies in the past have modeled land management or hurricanes as individual predictors, but disregarded the modeling of both components together. The current research aims to model both risk assessment and future hurricanes in developing an efficient forest optimization model that includes all the local factors and uses damage data from an existing hurricane to calibrate a prediction model. In this context, while damages from hurricanes have been determined, land managers could minimize risk of forest habitat damages.

Figure 1.1. Aerial view (left) of forest damage caused by Hurricane Felix (source: Inafor (2007)). Field view (right) of forest damage caused by Hurricane Felix (source: reprinted by permission of GIZ-GFA Consulting Group- MASRENACE(2010)).

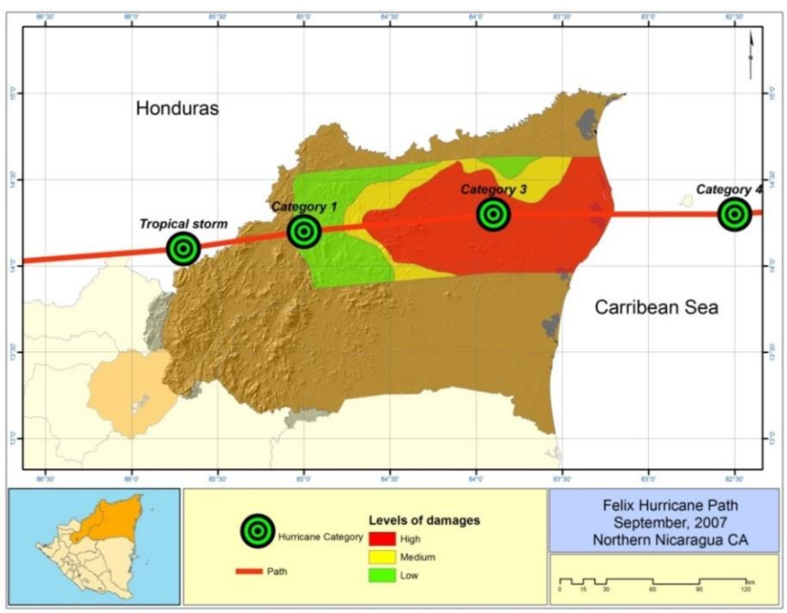


Figure 1.2. Trajectory, categories, and level of damages of the Hurricane Felix (September, 2007) (source: Inafor (2007))

1.3 Research Objectives

This study developed a forest optimization model (FOM) that produces a land management plan, which minimizes certain risk posed by hurricanes. The risk includes the damages to tropical forests (i.e., habitat disturbance) caused by hurricanes. The emphasis of the proposed FOM is on natural lands (e.g. forests management activities) rather than agricultural or urban - developed areas. The result of the FOM is a proposed plan that land managers (e.g., Institute of Forest Management from Nicaragua -- in Spanish, Inafor, -- local government, and hydrologic department) can use in formulating resource management plans for the regions under their care. This FOM determines which forest management activities (proposed by the land managers, Inafor and German Agency for International Cooperation - GIZ) will be assigned to spatially predefined management areas in order to minimize the negative impacts of hurricanes. The resulting FOM is able to locate the forest activities with species less susceptible to the hurricanes damages based upon some predefines constraints by users.

1.4 Rationale

The problem of land management in hurricane prone regions is that hurricanes result in many social, economic, and environmental impacts. Figure 1.3 portrays the gaps in the current literature that this research proposes to address. While Lin et al. (2008, 658-680) clearly demonstrates the relationship between flooding and landuse models (Figure 1.3 – 1), the inclusion of modeled hurricanes is required (Figure 1.3 – 3) before we can determine a more effective forest management plan. Moreover, the knowledge gap to be filled is the inclusion of the negative impacts of hurricanes (preconditions, assumptions) (Figure 1.3 – 2) in land management. This knowledge gap is filled using a forest management optimization model (Figure 1.3 – 4), which is subject to the constraints of available resources (i.e., budget) and the physical conditions (i.e., elevation, slope, distances from landfall). In sum, then, Figure 1.3 describes the conceptual model of a land management system for hurricane prone areas and the processes identified will be described throughout the remainder of this document. This research addresses a very relevant question: what mix of land use classes (e.g., broadleaf forest, pine, and forest fallow) will minimize the negative impacts of hurricanes?

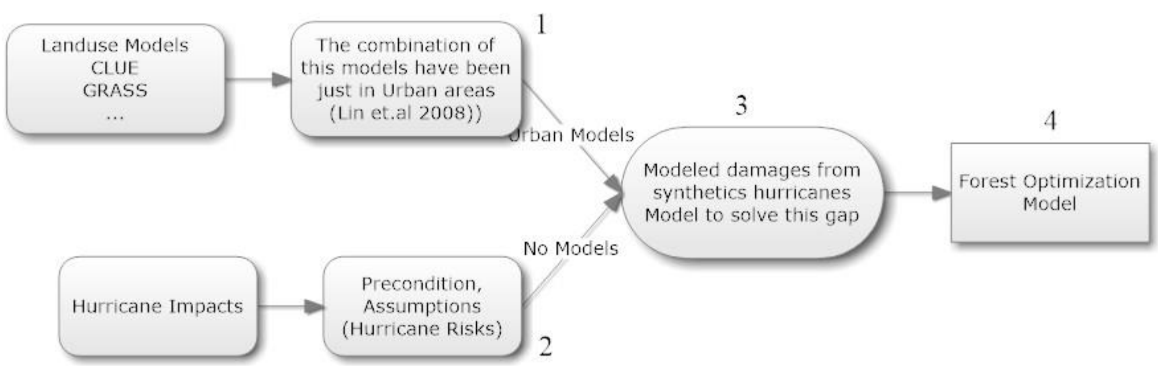


Figure 1.3. Flow chart portraying the lack of knowledge between the land management and hurricane impacts.

1.5 Background and Literature Review

McNulty (2002, S17-S24) addressed the positive and negative impacts of hurricanes on US forest carbon sequestration. This study was based upon carbon within the dead vegetation found in a forest, determination of downed biomass, and the impacts of hurricanes on long-term soil productivity and forest stocking. Other researchers, Stanturf, Goodrick, and Outcalt (2007, 119 - 135), implemented an unsophisticated matrix-based model (without spatial analysis) that provided a conceptual framework for managing forest disturbance caused by hurricanes. These also provided a very interesting list describing the susceptibility of tree species (pine and hardwoods) to damage from hurricanes (Rita and Katrina). Other studies (Irish, Resio, and Ratcliff 2008, 2003-2013; Kovacs, Blanco-Correa, and Flores-Verdugo 2001, 30-37) investigated the relationship between the characteristics of hurricanes to their impacts on specific types of forest. One prominent example by Uriarte and Papaik (2007, 519-528) used a spatially-explicit forest simulator (SORTIE). This study explored historical data of hurricane frequency and severity to build an appropriate disturbance regime for Southern New England. Next, they assumed an increasing trend in the long-term average frequency of severe hurricanes. Therefore, the majority of models presented (Stanturf et al. 2007; McNulty 2002) involving hurricane risks have not considered the spatially tropical forest disturbance by synthetic hurricanes as proposed in this current research.

In addressing the management forest disturbance caused by hurricanes, scientists have developed several spatial optimization models in order to decrease the strong adverse relationship between hurricanes and forest resilience. For instance, in recent years, some forest optimization models [known as Decision Making Model (Mendoza and Vanclay 2008)] have been created (Keles 2010, 468-474; Schneider 2008; Adams et al. 1996). Keles (2010, 468-474) created three forest optimization models based upon land management for carbon dioxide and timber production. The Keles (2010, 468-474) study was computed in a decision-support system ETCAP Optimizasyon (Keles 2010, 468-474), which was developed by the same researcher. In addition, Schneider (2008) performed a mathematical structure of the European Forest and Agricultural Sector Optimization Model. The model represents simultaneously observed resource and technological heterogeneity, global commodity markets, and multiple environmental qualities. Adams, et al. (1996), researchers of the United States Department of Agriculture, also developed a Forest and Agricultural Sector Optimization Model in the United States of America (FASOM). FASOM is a dynamic, nonlinear programming model of the forest and agricultural sectors. None of the previous forest optimization models spatially minimize the negative impacts of hurricanes in tropical forest disturbance.

1.6 Outline of the Modeling Approach

A forest optimization model (FOM) that reduces the adverse impacts posed by hurricanes is desirable. The need for improved land management in the eastern of Nicaragua provides the motivation to develop this FOM. As mentioned previously, the FOM is developed to incorporate spatially-referenced maps of the modeling area (Prinzapolka river watershed - section 2.3), modeled storm tracks, and local factors (e.g. landuse, topography, among others). This section provides a brief description of the FOM envisioned in this study.

The model is structured in three main components: (1) generation of synthetic hurricanes (SH) based on current data and models develop by (Emanuel et al. 2006, 299-314); (2) implementing a Damage Model Calibration (DMC) that assesses the level of damage caused by Hurricane Felix (2007) onto different forest classes and developing a Damage Prediction Model (DPM) combining SH and DMC results; and (3) developing a Forest Optimization Model (FOM) based on different SH that assigns land uses throughout the study area that minimize hurricane risks as described by the DPM results and applies various local and global constraints (Figure 1.4).

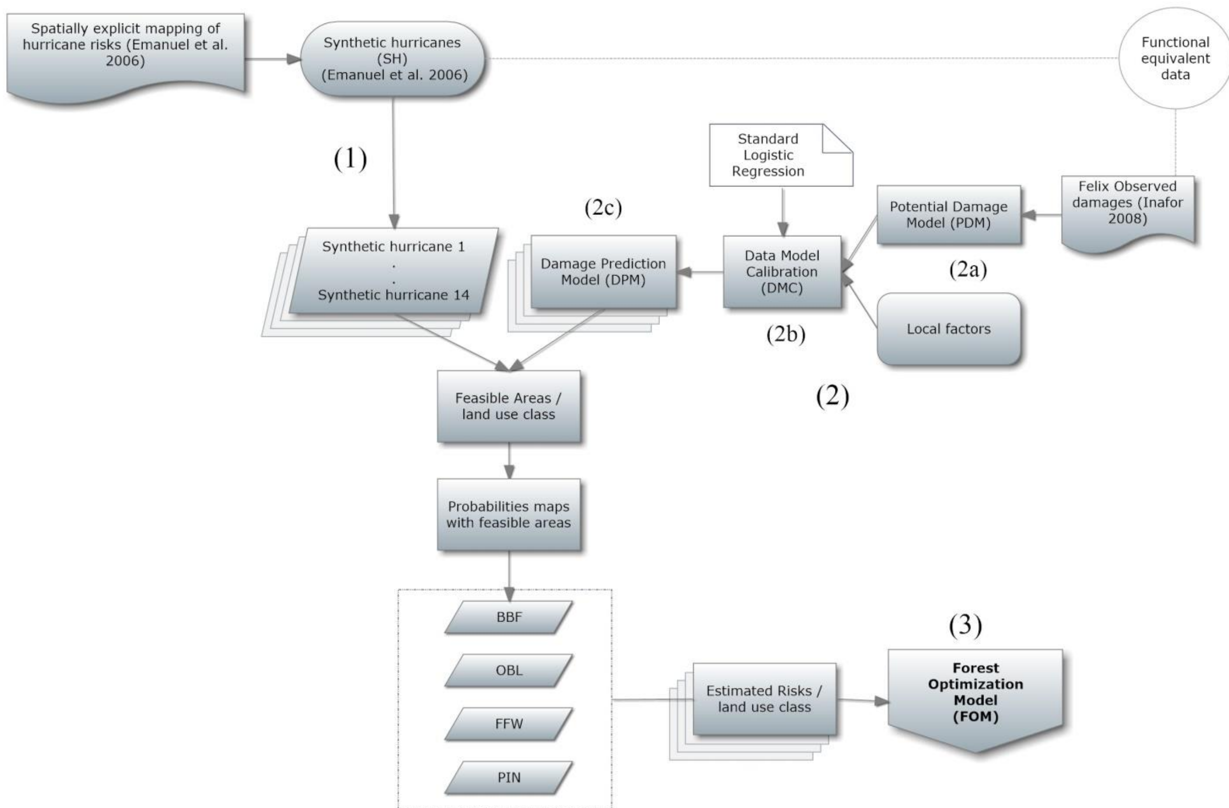


Figure 1.4. Flow chart portraying the first two main components of the forest optimization model: (1) generating synthetic hurricanes and (2) implementing damage model calibration using data from Hurricane Felix (2007) and developing a damage prediction model combining with synthetic hurricanes. These steps represent calibration and prediction steps of the model. The FOM step (3) is explained on the forest optimization model chapter (Chapter 5) (Figure 5.1).

First, the calibration and prediction study areas in Nicaragua are presented in Chapter 2. Then, the fundamental characteristics of hurricanes are discussed which allow to model potential damage and to simulate synthetic hurricanes. A selection of a total fourteen manageable number of synthetic hurricanes (Chapter 3) was made to implement the FOM using the synthetic hurricanes, (Figure 1.4 – 1). The chosen synthetic hurricanes; (1) overlay the eastern coastline of

Nicaragua, (2) are stratified based on intensities of hurricanes, (3) are spatial distributed in the predicted area, and (4) are distributed in wide temporal frame.

The second component (Figure 1.4 – 2), which represents the damage calibration and damage prediction models of the FOM, are developed and introduced in Chapter 4. The collected data after Hurricane Felix (2007) with functional equivalent data was applied for calibration. Due to the nonlinear relationship between wind speed and distance from a storm track, a potential damage model (Figure 1.4 – 2a) was implemented using wind speed and distance from Hurricane Felix path. Then, a logistic regression model of damage rates for each land cover was implemented (Figure 1.4 – 2b). Local factors, which are potentially related to the destructive power of hurricanes, were tested as explanatory variables. The damage prediction model (Figure 1.4 – 2c) aims to predict the potential damage of synthetic hurricanes as input for each hurricane in future time within the feasible growth area of each land cover. This risk assessment (component 2) involves stochastic approach because of the estimation of probability distributions based on different hurricanes.

On the other hand, the FOM (Figure 1.4 – 3), which is executed in Lingo optimization software, is extensively discussed in Chapter 5. The risk assessments of fourteen synthetic hurricanes for each landuse class are input in the FOM. The FOM is expected to produce a land management allocation solution that optimizes land use management subject to different sets of constraints. The FOM is a deterministic optimization method because of the expectation of identical results with same inputs. In this research, the FOM deals with solving a linear programming problem, where the decision variables are continuous values (e.g., probability values). Then, because risk prediction depends on landuses, an optimization of landuses (as the objective function) will be made to reduce those risks posed by hurricanes (FOM). Even though the complete analysis is a complex model, this proposed investigation is mainly a combination between two research methodologies; stochastic and deterministic optimization methods. Finally, the conclusions for future research are presented in the Chapter 6.

CHAPTER 2

DATA AND FORESTRY OF THE STUDY AREA

This chapter introduces the collected data and the characteristics of the forest (landuses) in the study area. The study area is managed by Forestry territorial planning of RAAN and RAAS, whose managers are representative of Inafor, local governments, and indigenous communities. The landuse of 2005, which is the landuse before Hurricane Felix, and the damage data collected after Hurricane Felix hit the study area are presented. To be incorporated in the DMC and DPM, the landuses had to be aggregated in six landuse classes. Then, two land-covers were excluded because of insufficient sample points and non-forest land cover. The four landuse classes (BBF, OBL, FFW and PIN) (Figure 1.4) implemented in this FOM are explained below.

2.1 Study Area of calibration model and area prediction model

The proposed FOM is implemented on the east coast of Nicaragua (RAAN and basin Prinzapolka River watershed) (Figure 2.1). This study area was selected, because of its natural resources, indigenous communities, and the occurrences of catastrophes (e.g., flooding and hurricanes). In order to calibrate and model the forest optimization, two areas, a training and prediction area with similar environmental conditions (historical tropical storms) were chosen. These study areas are detailed described in this section.

Figure 2.1. Map of eastern Nicaragua with the calibration area (Hurricane Felix area damage) and proposed prediction area (basin Prinzapolka River, and track of Hurricane Felix (2007) are presented.

The eastern topography of Nicaragua is a transition area from coastline distance of ~ 100 km between flat area in the East to mountainous areas in the West. The soils of the RAAN, which are classified into seven Orders, are most frequently acid to very acid. The Orders of Ultisol and Oxisol dominated the study area. The effective soil depth varies from moderate to very deep (40-60 cm to over 100 cm), and they change over time to the process of erosion. Due to leaching (high rainfall) and high concentrations of aluminum and manganese (pH acidic to very acidic), these soils have very-low to low levels of fertility. The soil textures are predominantly clayey and very friable. The weather conditions are typical humid tropical ecosystem where rainfall ranges from 2,500 to 4,000 mm/year. Temperatures are warm tropical in the lowlands (25-27 °C) and milder in the mountainous areas (22-25 °C). From 1953 to 2013, twenty-four hurricanes have been recorded and making landfall in the RAAN (Figure 2.2).

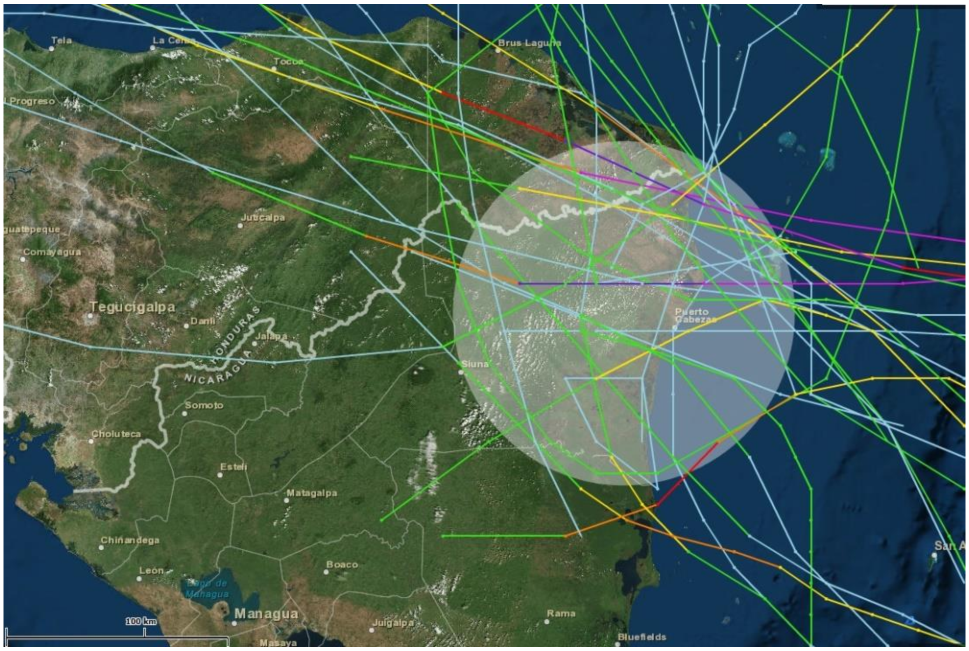


Figure 2.2. Historic hurricane tracks in the study area of RAAN (source: Image from the NOAA Office for Coastal Management Historical Hurricane Tracks web site, http://coast.noaa.gov/hurricanes)

2.1.1 Area of calibration model: Hurricane Felix damage path

The calibration area to estimate the damage model is located in northeastern Nicaragua. This was the area impacted by Hurricane Felix (2007), which caused severe damages to the forest, flooding, and infrastructure. It is bordered by the country of Honduras (north), the RAAS and basin Prinzapolka River (south), the Caribbean Sea (east) and Jinotega (west). As seen in Figure 2.1, all the storm damage lies in this calibration area in RAAN. Most people live in the rural area (73%) with a very low population density of 9.5 Pop. per km^2 (compared with 43 Pop.

per km^2 average in Nicaragua). In this calibration area, the major city is Puerto Cabezas (in Miskito language Bilwi) located in the Caribbean coast. The population of this region is multicultural and consists of 42% mestizo, 40% of Miskito, 10% Kriols (or Creole), and 8% Mayangna. Before Hurricane Felix, the most significant land cover was broadleaf forest (dense broadleaf forest with 55% and open broadleaf forest with 12% of the total area). The eastern part of the calibration area contains some land cover of shrubland and emergent herbaceous wetlands. This portion consists of major flooding areas due to low elevation and a high presence of precipitation and this area has a very limited existing road network at its north-west side.

According to Inafor (2007), the damages caused by Hurricane Felix were invaluable. It significantly altered the whole life of indigenous communities of this region and impacted the communities of Kukrira, Bismuna, Pahra, Tuapi, and Sandy Bay, which suffered severe damage. Moreover, Felix also affected the economy and paralyzed the efforts that residents have been making to escape poverty in this region. The important data collected by GIZ and INAFOR after Hurricane Felix is employed to calibrate the model (section 2.3.2).

2.1.2 Area of prediction model: Basin Prinzapolka River

The Prinzapolka River basin serves as prediction area. Its environmental conditions are similar to those of the calibration area (i.e., comparable areas percentages of landuses classes, indigenous communities, and the presence of past hurricanes). Moreover, after Hurricane Felix, severe flooding occurred in the Prinzapolka River mouth, which is located in the lower basin of the study area (ACAN-EFE 2007; Morel 2007). This selected area is the Nicaraguan National Basin named 53 with an extent of 10,599 km^2 and average precipitation of 2,661 mm/year. Located in northeastern of Nicaragua, the prediction area is bordered by calibration area (north), the RAAS (south), the Caribbean Sea (east) and Matagalpa - Jinotega (west). It shares the major city with the calibration area, Puerto Cabezas, which is located just north of the mouth of the Prinzapolka River. Parts of the prediction area belong to RAAS.

2.2 Forestry

The forest management can be approached from several perspectives (Li et al. 2011). Hence, to implement the FOM, the professional forest management perspective, which implements some techniques to assist selecting management alternatives (Li et al. 2011), has been considered. Undoubtedly, to aid forest management, any planned management has to consider both resources and natural disturbances. With respect to these resources, forest management includes the characteristics of species, such as the adaptation to new conditions, soil, elevation, and slope. With respect to natural disturbances, forest management considers all potential disturbances, such as flooding, hurricanes, wildfire, volcanic eruption diseases, and windstorms.

To enhance the forest management of any region, the inclusion of existent land-cover (or forest activities) is crucial for prominent results. Broadleaf forest (or hardwood) in the mountainous areas and pine forest and wetlands in the flat area (east of RAAN) dominate both the calibration and prediction areas. Table 2.1 summarizes the land uses of 2005 before Hurricane Felix occurred in 2007 (Figure 2.3). The focus of this research is on forest optimization; therefore, the landuses not related to forest activities (such as wetlands, shrubland, cultivated crops, among others) were aggregated into one unspecified land-cover class.

Table 2.1. Description of the land uses in the study area (RAAN) before the Hurricane Felix (source: Inafor (2007); GIZ-GFA Consulting Group- MASRENACE (2010)).

Land use	**Description**
Dense Broadleaf Forest	This land cover refers to angiosperms (broadleaf), which has the characteristics of being heavily wooded. This forest covers more than 70% canopy cover with trees greater than 15 m height (depending on age and phenological development of each species). It also has a variety of plant species in different strata and grows in humid climates with rainfall exceeding 2,000 mm/year. 
Open Broadleaf Forest	It has similar characteristics as the broadleaf forest in terms of structure and type of species. However, human intervention is remarkable with a percent canopy cover from 30% to 70% and the open spaces are frequently covered with natural regeneration of these species in the forest. 

Table 2.1 continued

Land use	Description
Mixed Forest	It mainly refers to the combination of broadleaf forest and pine. The identification of this coverage is very subjective as it may present predominance of one or another forest. The dominant species are *Pinus oocarpa* and *Quercus spp*. (GIZ-GFA Consulting Group- MASRENACE 2008)
Forest fallow (tacotal)	This land cover is a transient state of forest succession, and it represents the recovery of the forest when it has been involved in the establishment of crops and/or grazing. The forest fallow is very similar to a secondary forest, which is usually described by species of medium size. 
Dense Pine Forest	This land cover is exclusively dominated by Coniferous species of *Pinus caribeae var*. The dense pine cover can be found at the northeast of the RAAN, near rivers forming pure source patches (Stevens 2014). 

Table 2.1 continued

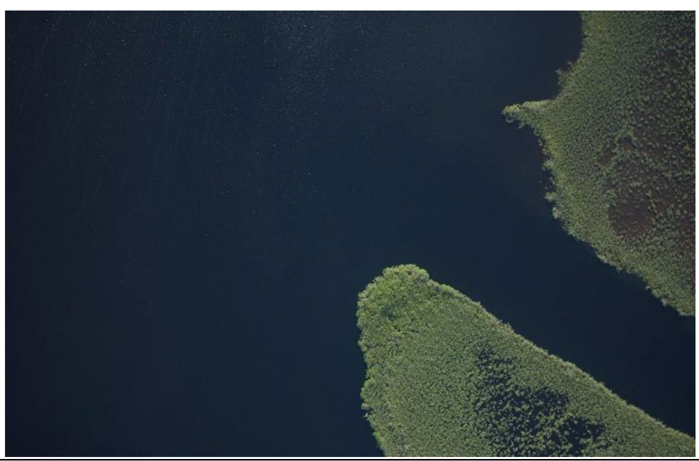
Land use	**Description**
Open Pine Forest	Coniferous species with considerable spacing between trees characterize this forest. This vegetation type is strongly associated with human activities, especially fires. In addition, it is commonly considered as a stage of forest succession. These forests are regularly found in the upper and middle slopes but are often replaced by evergreen forests on the peaks and valleys (Stevens 2014). 
Mangrove	The limits of mangroves are defined as a result of periodic immersion in salt water, due to tides. The trees found in the mangroves are highly adapted and restricted to this environment. The species of mangrove forest, such as *Rhizophora mangle*, *Avicennia nitida*, *Laguncularia racemosa*, among others, are usually found next to the bodies of marine water, estuaries, and river mouths. 

Table 2.1 continued

Land use	Description
Shrubland - Wetlands	These areas are not considered forest covers. It consists mostly pastures or crops or a combination of both. These grasses can be managed or not, cultivated or grow naturally. The predominant activity in these areas is ranching, and these areas are localized mainly in the flat areas or valleys. However, these areas can also be found on mountain slopes with scattered trees.

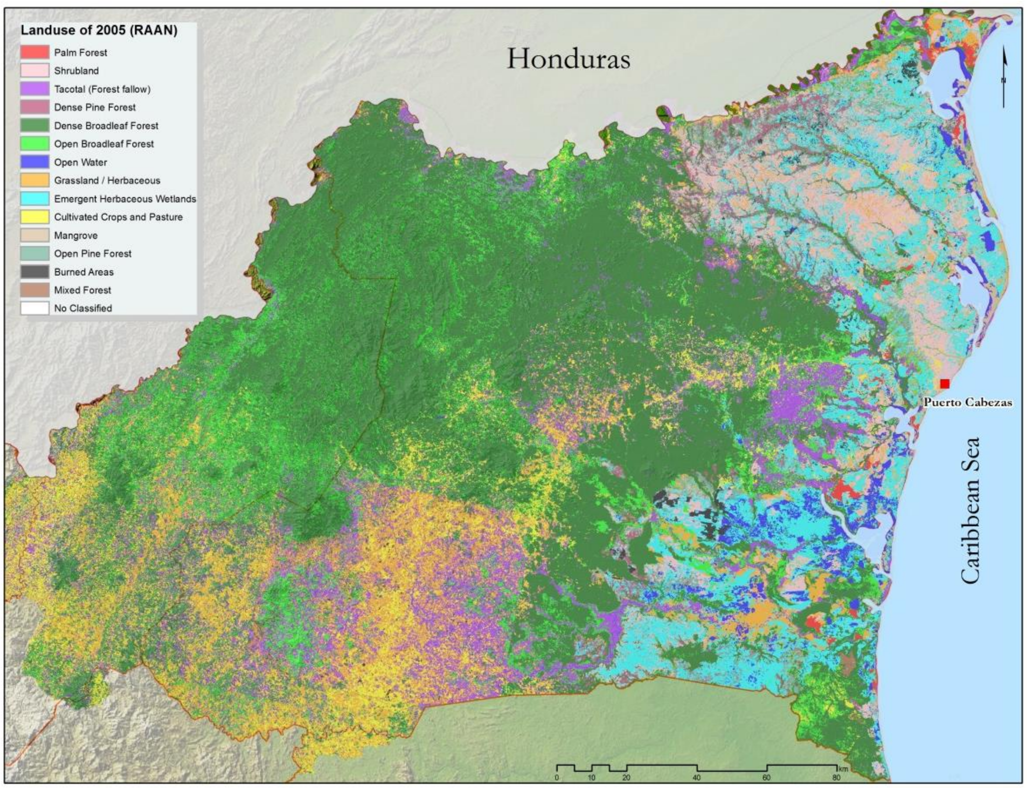


Figure 2.3. 2005 land use pattern in eastern of Nicaragua before the Hurricane Felix hit RAAN in 2007 (source: GIZ-GFA Consulting Group- MASRENACE (2008)).

According to Stanturf et al. (2007, 119 - 135), in natural ecosystems, the relation between forest features and site characteristics form a complex condition against hurricanes. Based on the characteristics of each land cover presented in the Table 2.1, the behavior of these landuses can be explained in the presence of damage from tropical hurricanes. The susceptibility to hurricane damages of the land covers will depend on the resistance of the canopy structure. Zimmerman et al. (1994, 911-922) suggests that a forest with mature or larger trees is more likely to be damaged by a hurricane, than a forest with small trees. For instance, dense broadleaf forests are more susceptible because they provide more wind resistance (70% canopy cover and trees greater than 15 m height). In contrast, pine forests, either dense or open, provide less resistance to the impacts posed by hurricane winds because of the considerable spacing between trees and the presence of low percent canopy cover in coniferous.

2.3 Data preparation

Hurricanes, which are a fact of life in eastern Nicaragua, can be characterized with respect to their path, wind speed, central pressure, and rainfall intensity. In this section, the data preparation of Hurricane Felix (Figure 2.4) and data collected after Hurricane Felix are presented (Figure 2.5 and Figure 2.6). The original landuses were aggregated into six landuse classes based upon similar characteristics (i.e. they demonstrate similar responses to hurricanes damages). The aggregation classes ensured that sufficient number of sample location for each landuse class were available to adequately calibrate the prediction model.

2.3.1 Hurricane Felix (2007)

According to the Tropical Cyclone Report (Beven 2008), Hurricane Felix was formed by a tropical wave that departed the coast of Africa on August 24, 2007 (Figure 2.4). It was a small, but powerful, category five hurricane (on the Saffir-Simpson Hurricane Scale) that caused major damage in northeastern Nicaragua. Felix was a hurricane category 5 when made landfall near Punta Gorda, Nicaragua at 12 UTC, September 4 (2007). Furthermore, by that time, Puerto Cabezas reported sustained winds of 44 kt at 1300 UTC on September 4 (2007) (Beven 2008). The observed trajectory information of Hurricane Felix is employed in the data calibration model. It is assumed that Hurricane Felix characteristics, such as wind speed (kt), trajectory speed (duration), pressure (mb), and precipitation (in), contribute to the level of damages. These factors are known in the FOM as functional equivalent data with synthetics hurricanes (Emanuel et al. 2006, 299-314) for prediction purposes.

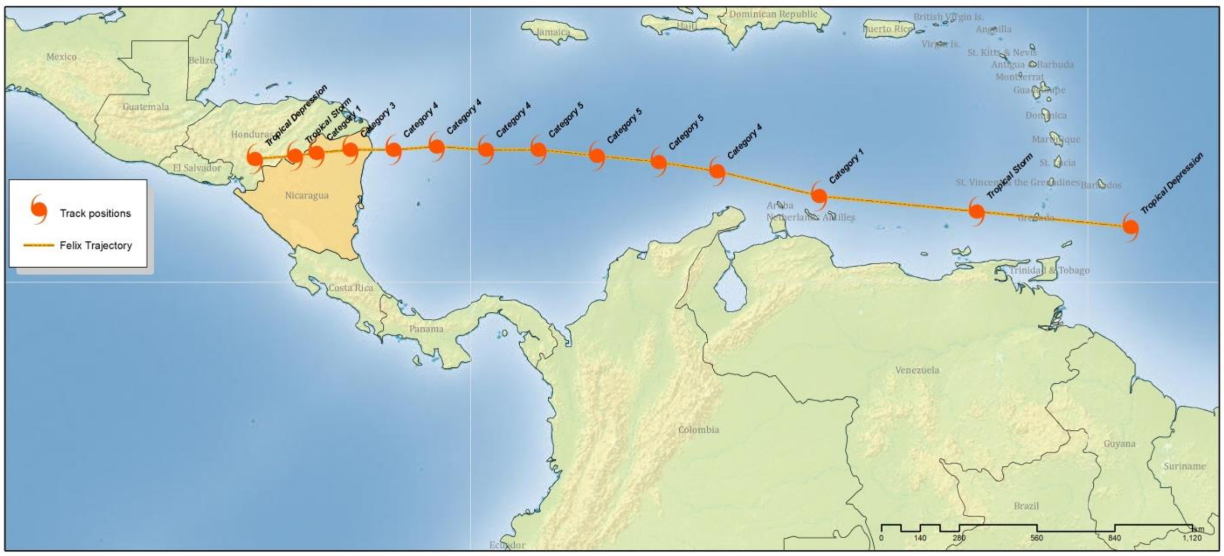


Figure 2.4. Track for Hurricane Felix, 31 August – 5 September 2007 (source: National Hurricane Center, Beven (2008), and Inafor (2007)).

2.3.2 Forest Damage Assessment

After Hurricane Felix made landfall, the regional government of RAAN in coordination with Inafor and with the support of international organizations (i.e., GIZ, FAO, and WWF) proposed to carry out a comprehensive assessment of forest ecosystem damage caused by Hurricane Felix (2007). First, surveillance flights over the impacted area acquired digital aerial photographs (called tiles) and identification of levels of ecosystem damages. Damage assessment was based upon human judgment by two forest evaluators who conducted a visual record of the damage during flights. These damage levels represent the percentage area damaged for each evaluated photo and damage levels are assigned on a range of 1-5 (example of aerial photos of each level of damage are presented in Figure 2.5). Then, a field assessment through targeted sampling areas was conducted to quantify ecosystem damages.

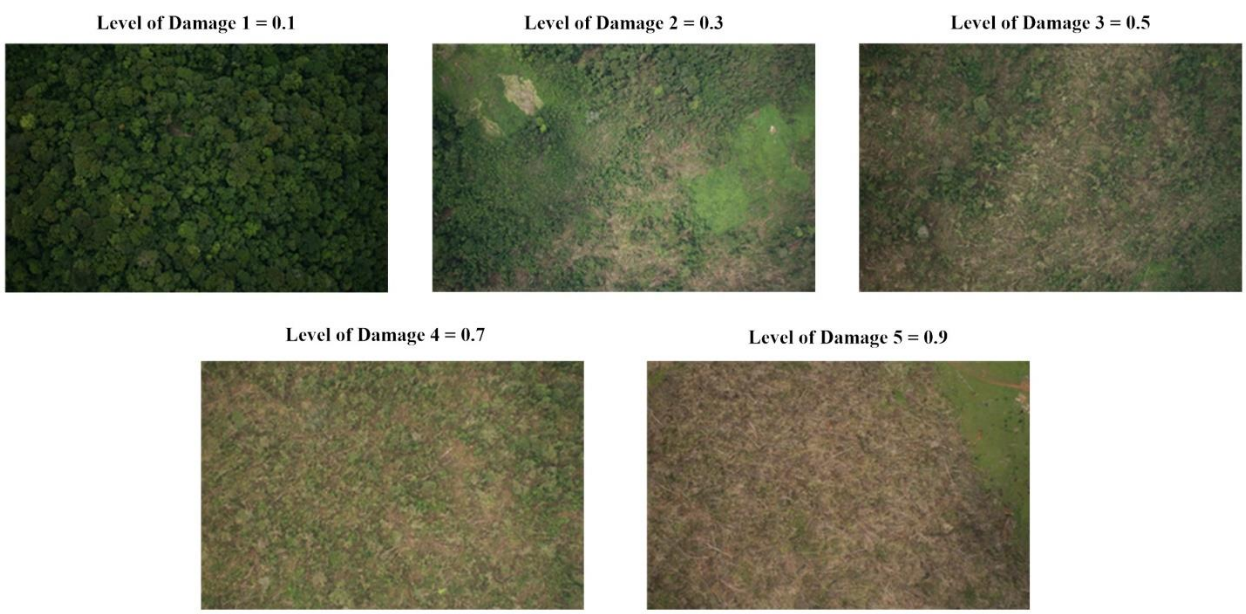


Figure 2.5. Examples of aerial photos collected by Inafor after Hurricane Felix (2007) of each level of damage (Inafor 2007).

The sample data gathered (tiles) after Hurricane Felix is not a random sample, but a systematic sample following a convenient flight path zigzagging along Felix's trajectory (Figure 2.6).This sampling scheme did not control for landuse and therefore some landuse are either over- or under-sampled and, in addition, exposed to different degrees of damage intensity. The total 1,611 sample tiles from this forest assessment of damages are shown spatially distributed in Figure 2.6. The 2005 landuses (Figure 2.3) of the field assessment were aggregated into six landuse classes based upon similar responses to hurricanes damages (Table 2.2). These six landuses classes are presented spatially distributed in Figure 2.6. The response variable, a subjective assessment of damage rates obtained from tiles of aerial photographs (Figure 2.5), lists five ascending levels of damage severity. To run a logistic regression, these levels of damage were transformed into equivalent damage probabilities for each sample point (0.1 – 0.9).

However, previous descriptive statistical analysis suggested excluding two land cover classes, both mangrove and shrubland–wetlands. First, mangrove is found in the buffer coastal zone and does not contain a sufficient number of observations for statistical analysis (27 observations) (Table 2.2). Additionally, mangrove does not have economic value and is located in flat land and flooding areas. Secondly, even though land-cover class shrubland–wetlands consists of a considerable number of observations (361), it was not considered in the analysis because it is a mix of non- forest landuses (i.e., emergent herbaceous wetlands, shrubland, cultivated crops and pasture, grassland / herbaceous, and palm forest). If a statistical analysis is implemented in shrubland–wetlands landuse class, the damage prediction obtains inaccurate results as presented in the quality control in Figure 2.7. In addition, due to the topography of the area, the sample of shadow mountain observations was excluded. The shadow mountain observations were excluded because do not influence in the analysis. They are located beyond the highland and hurricane damages are expected to be minimal. Based on the flight paths of the damage assessment, the flight-in sample points, which are the observations at the beginning of the flight path, were also excluded. These tiles presented inaccurate damage assessment. Consequently, removing the observations of both mangrove and shrubland–wetlands and the shadow mountain, the number of valid sample points decreased from 1,611 to 955. The remaining sample points (955) are tabulated by landuse and level of damage in Table 2.3.

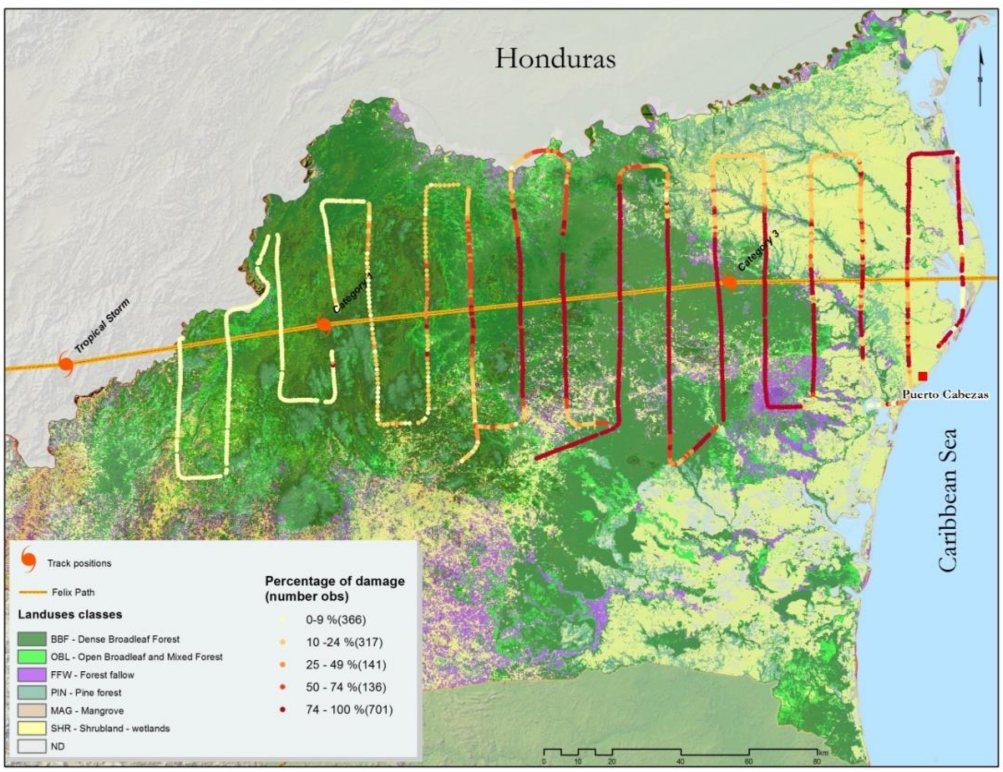


Figure 2.6. Map of spatial data of assessment damage rate (five levels of damage from 1-5 and converted to probabilities values) after Hurricane Felix by Inafor (2007) and the landuses classes (2005) before Hurricane Felix.

Table 2.2. Land cover classes with number of observations in each damage category (five level of damages).

Landuse class	**Damage (%)**	**Obs**	**Lu Class**	**Damage (%)**	**Obs**
Dense Broadleaf Forest	0-9	222	Pine Forest	0-9	0
	9-24	103		9-24	28
	25-49	70		25-49	9
	50-74	67		50-74	8
	74-100	392		74-100	11
Broadleaf Forest and Mixed Forest	0-9	81	Mangrove	0-9	1
	9-24	29		9-24	0
	25-49	13		25-49	4
	50-74	19		50-74	3
	74-100	50		74-100	19
Forest fallow	0-9	20	Shrubland–wetlands	0-9	21
	9-24	12		9-24	142
	25-49	4		25-49	38
	50-74	12		50-74	24
	74-100	71		74-100	138

Table 2.3. Restricted damage counts after removing mangrove and shrubland–wetlands and shadow mountain observations.

Lu Class	Damage (%)	Obs	Lu Class	Damage (%)	Obs
Dense Broadleaf Forest	0-9	82	Forest fallow	0-9	3
	9-24	81		9-24	12
	25-49	64		25-49	4
	50-74	67		50-74	12
	74-100	371		74-100	70
	Total	665		Total	101
Broadleaf Forest and Mixed Forest	0-9	34	Pine Forest	0-9	0
	9-24	26		9-24	27
	25-49	13		25-49	9
	50-74	19		50-74	8
	74-100	42		74-100	11
	Total	134		Total	55

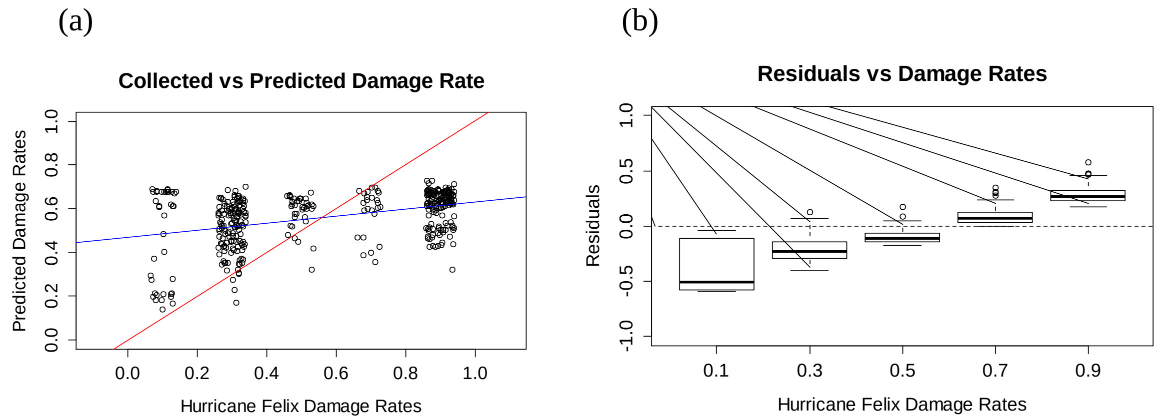


Figure 2.7. Quality control graph by comparing observed damage rate of Hurricane Felix and predicted damage rate using DPM. (a) Plot of measured damage rates and predicted damage rates for land cover shrubland–wetlands. (b) Boxplot of measured damage rates and residuals after applying the Data Prediction Model for land cover shrubland–wetlands.

For the DPM, the feasible growth areas for each land cover class had to be determined. Supported by a soil expert, a deterministic analysis to limit the feasible growth areas for each land cover class was performed (Figure 2.8). The subgroup soil map (Tahal Consulting Engineers and Tecnoplan 1978, 1-197), which includes the order, suborder and great group, was overlayed with the terrain slope (%) to determine feasible growth areas for each land cover class. For instance, overlaying the subgroup Typic Hapludalfs with a slope range of 8-45% defined a portion of Pine feasible area. Accordingly, in the prediction area, the entire area of Prinzapolka river watershed (10,599 km^2) is feasible for land cover class dense broadleaf forest and open broadleaf forest. In contrast, the feasible growth area of forest fallow, which is located in the middle and high part of the watershed, covers 3,919.50 km^2 (40%) of the study area. Also, the feasible growth area for pine, which is placed in the flat and central part of the watershed, covers 1,762.63 km^2 (17%).

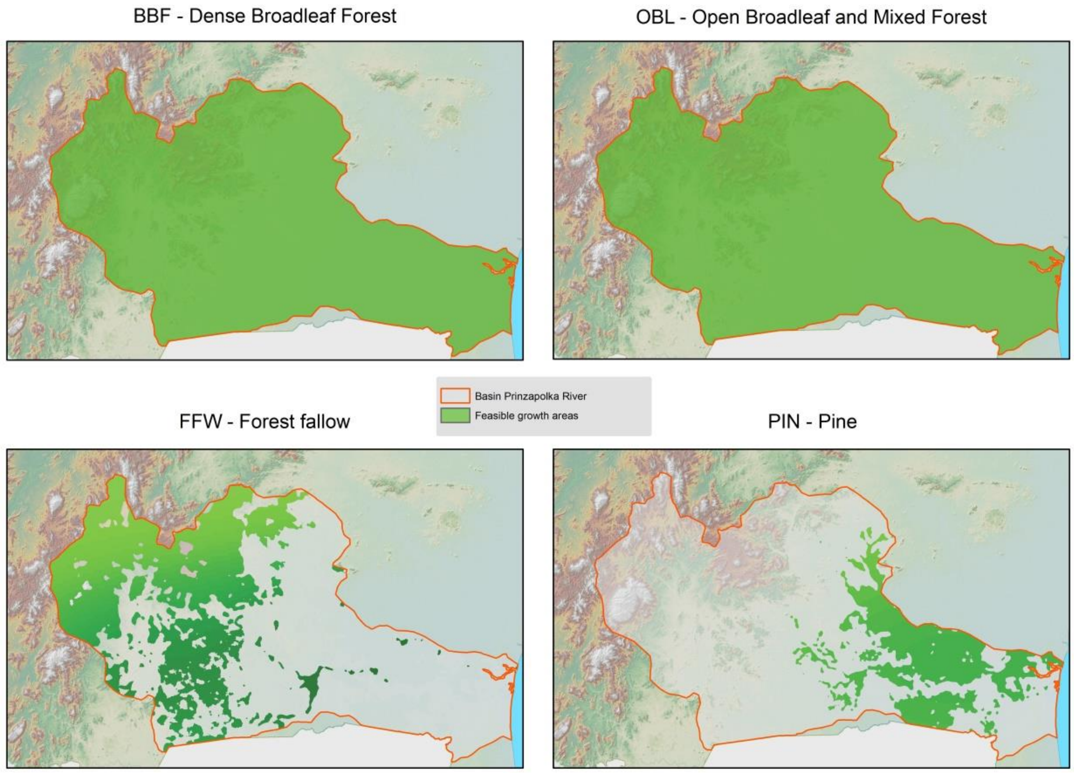


Figure 2.8. Feasible growth areas for four landuses classes to implement the Data Prediction Model.

CHAPTER 3

PRINCIPLES OF HURRICANES AND SYNTHETIC HURRICANES

This chapter provides a discussion of the impact of hurricanes onto the forest in eastern Nicaragua. Furthermore, its destructive components (i.e., precipitation, storm surge, and winds) are discussed. This chapter also explains the generation of synthetic hurricanes, which was developed by Emanuel et al. (2006, 299-314) (Figure 1.4 – 1).

3.1 Underlying meteorology of hurricanes

As mentioned in the introduction, hurricanes are expected to increase in frequency and severity (Webster et al. 2005). It is known that tropical hurricanes in Nicaragua originated in the Atlantic Ocean. Stanturf et al. (2007) specified three primary sources of energy leading to the development of hurricanes: the coast of West Africa, the Caribbean Sea or the Gulf of Mexico. June 1 to November 30 defines the official season of hurricanes in the Atlantic basin (the peak of the season is the middle of August to late October) (National Weather Service 2014).

Stanturf et al. (2007) identifies three features: precipitation, storm surge, and winds as prime sources of hurricane damage. Stanturf et al. (2007) also admits that the hurricane feature of wind is directly related to most storm disturbances. Further, a combination of low pressure and high wind (Stanturf, Goodrick, and Outcalt 2007, 119 - 135) explains the counter clockwise rotation of the hurricanes (the coriolis effect) in the northern hemisphere. Consequently, in an attempt to understand the negative impact of hurricanes, Figure 3.1 links the hurricane characteristics (i.e., wind speed, distances from path and landfall) with local factors. In Figure 3.1, the vector V_P (velocity of path) represents the speed of a hurricane track. The vectors V_R (right velocity) and V_L (left velocity) represents the speed of a hurricane in the right-hand and left-hand sides, respectively. Therefore, based on the coriolis effect, the vector $V_P + V_R$ (additive vectors) suggests that the speed of the hurricane and the hurricane rotation can add each other and therefore expected more damage. In the left-hand side, the vector $V_P – V_L$ represents how the speed of the hurricane and the rotation subtracted from each other. Therefore, less damage in the left-hand side of the hurricane route is expected.

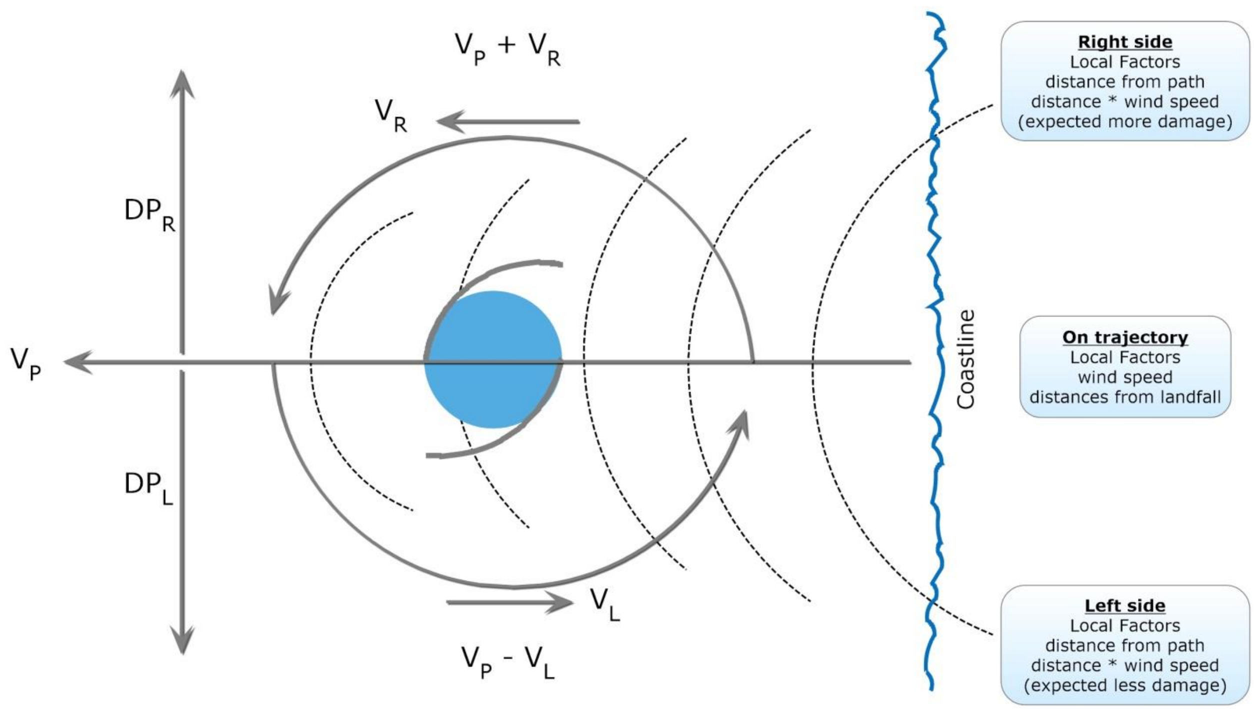


Figure 3.1. Diagram of interaction of local vulnerability measures variables (local factors) and hurricane characteristics on trajectory, right side, and left side of hurricane.

Once hurricanes reach landfall (Figure 3.1 – the coastline), both extensive rainfall and high wind speeds are expected (Stanturf et al. 2007). Besides local factors (i.e., landuses, topography, among others), once a hurricane makes landfall, two distances become associated in forest damages, the distance from hurricane landfall (V_P) and path (DP_R and DP_L). On V_P distance, as a hurricane moves inland (specifically the mountainous areas), the potential damages are diminished. On the DP_R and DP_L, it is expected the higher forest damages located a short distance from hurricane track. For instance, the forest damage assessment (Figure 1.2 and Figure 2.6) characterizes, depending on vegetation, the lowest forest level of damages in greater distances from both coastline and path.

3.2 Simulation model of Synthetic hurricanes

This section describes the combined statistical and deterministic approach to hurricane risk assessment article published in American Meteorological Society by Emanuel et al. (2006), a professor of Atmospheric Science at the Massachusetts Institute of Technology (MIT). Recognizing the existence of this intensive algorithm to model past and future hurricanes in Central America, the aim was to generate future hurricanes and their characteristics to estimate the damage pattern in the landuse classes. The presented hurricane risk assessment is a combination of statistical track generation with deterministic intensity model to generate synthetic hurricane. It is using a compilation of historical genesis points derived from track data (1970 to 2005) from the National Hurricane Center (Figure 3.2).

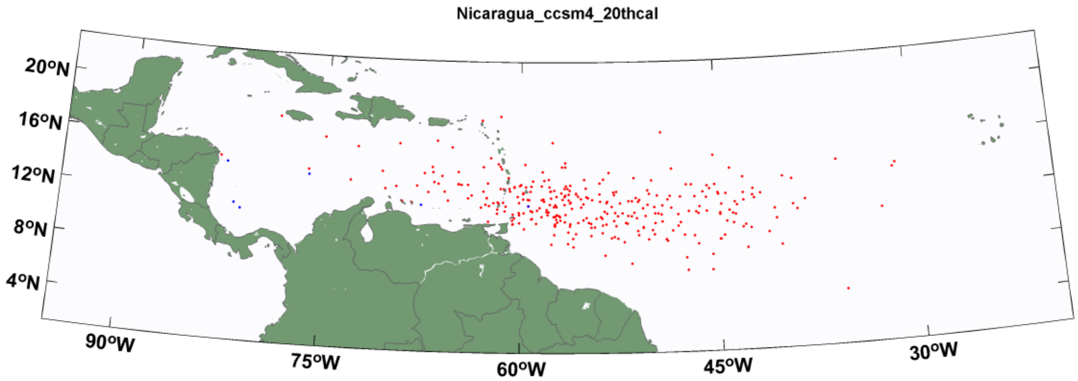


Figure 3.2. Historical genesis points derived from tropical cyclone best-track data on “A statistical and deterministic approach to hurricane risk assessment” developed by Emanuel et al., 2008. This simulation adopts the Community Climate System Model v.4 for the years of period 1950-2005.

Fortunately, a MatLab code including multiple models (e.g., CCSM4, GFDL5, HADGEM5) and types (e.g., 20th, rcp85, and reanal) to generate the synthetic hurricanes for Central America was available. This program was compiled to retrieved synthetic hurricanes portraying in Figure 3.3. In this approach, the models (and type) generated a specific number of synthetic hurricanes. The Community Climate System Model version 4.0 (CCSM4) is a coupled climate model for simulating the earth's climate system (Gent et al. 2011, 4973-4991). The CCSM4 data model was utilized to investigate a number of potential synthetic hurricanes in parts of Central America. These simulated synthetic hurricanes are required to touch the Caribbean coast of Nicaragua. Depending on the model and type, the number of hurricanes ranged between 560 to 950 synthetic hurricanes (Figure 3.3).

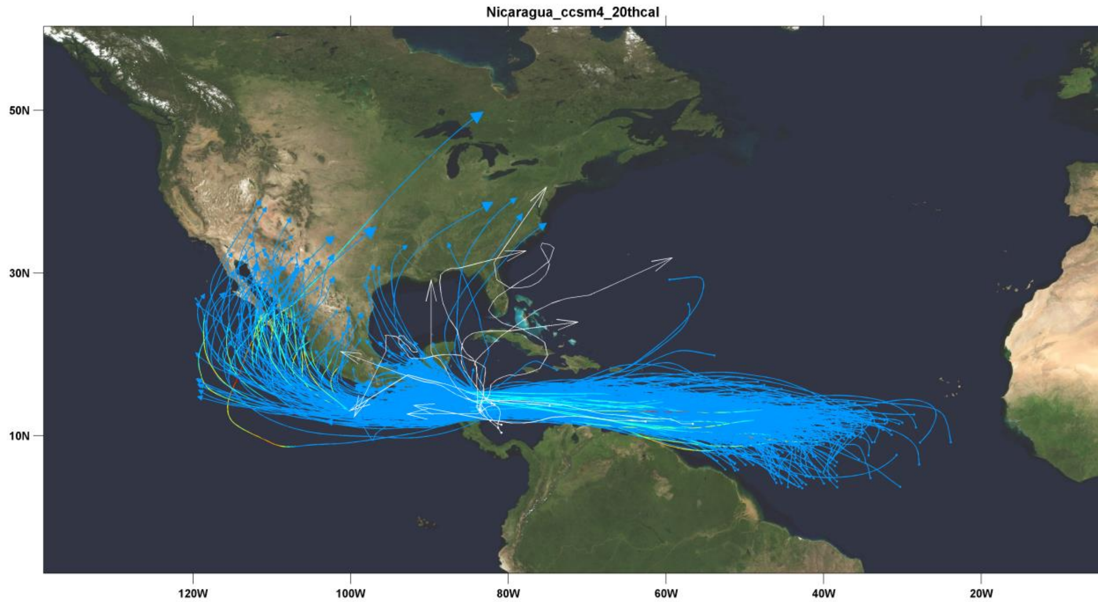


Figure 3.3. Modeling hurricanes trajectory in the Northeastern of Nicaragua using “A statistical and deterministic approach to hurricane risk assessment” developed by Emanuel et al. (2008). This simulation adopts the Community Climate System Model v.4 (Gent et al. 2011, 4973-4991) for the years of period 1950-2005.

As reported by Emanuel (2013), to simulate synthetic hurricanes, the tracks were filtered so that each hurricane modeled trajectory passes through at least one of the connected line segment of the Caribbean coast of Nicaragua. Then, the tracks were downscaled from each of a handful of climate models; for two periods: the 20th century (1950-2005) and rcp85 (2006-2100). Each of the models has been scaled to give the same overall rate of occurrence for the 20th-century simulations. Each event set contains a documentation that explains the resulting variables for the simulation. The attributes data retrieved from this simulation are functional equivalent data gathered following Hurricane Felix, such as trajectory (direction) and wind speed.

Finally, to implement the FOM using the synthetic hurricanes, a selection of a total fourteen manageable number of hurricanes was made (Table 3.1 and Figure 3.4). The selected hurricanes are from the model RCP85, which is the scenario known as Representative Concentration Pathways (RCPs). It uses the evolution of the atmospheric composition for the remainder of the 21st century (Meinshausen et al. 2011, 213-241). The chosen synthetic hurricanes are: (1) overlayed on the eastern coastline of Nicaragua, (2) stratified based on intensities of hurricanes, (3) spatial distributed in the prediction area, and (4) distributed in a wide temporal frame (2015 - 2091).

Table 3.1. List of selected synthetic hurricanes to be modeled in the FOM (source: Emanuel et al. (2006, 299-314)).

No	Track	Model	Date	Categories	Windspeed (knots)	Group of hurricanes
0	Felix	-	Sept 2007	3-5	-	-
1	099	RCP85	Aug 2015	3	38-96	5, 10 and 14
2	110	RCP85	Aug - Sept 2016	5	60-140	5, 10 and 14
3	125	RCP85	Aug - Sept 2018	3	50-100	5, 10 and 14
4	138	RCP85	Sept 2019	3	64-96	5, 10 and 14
5	150	RCP85	Sept 2020	3	51-102	10 and 14
6	248	RCP85	Sept 2030	5	58-150	5, 10 and 14
7	250	RCP85	Sept 2030	3	42-86	10 and 14
8	251	RCP85	Sept - Oct 2031	4	65-125	14
9	291	RCP85	Aug 2035	5	69-139	10 and 14
10	309	RCP85	Aug 2036	5	56-145	10 and 14
11	373	RCP85	Aug - Sept 2043	4	68-122	14
12	534	RCP85	Aug 2059	5	77-138	14
13	665	RCP85	Aug 2072	4	68-116	10 and 14
14	856	RCP85	Aug 2091	4	63-117	14

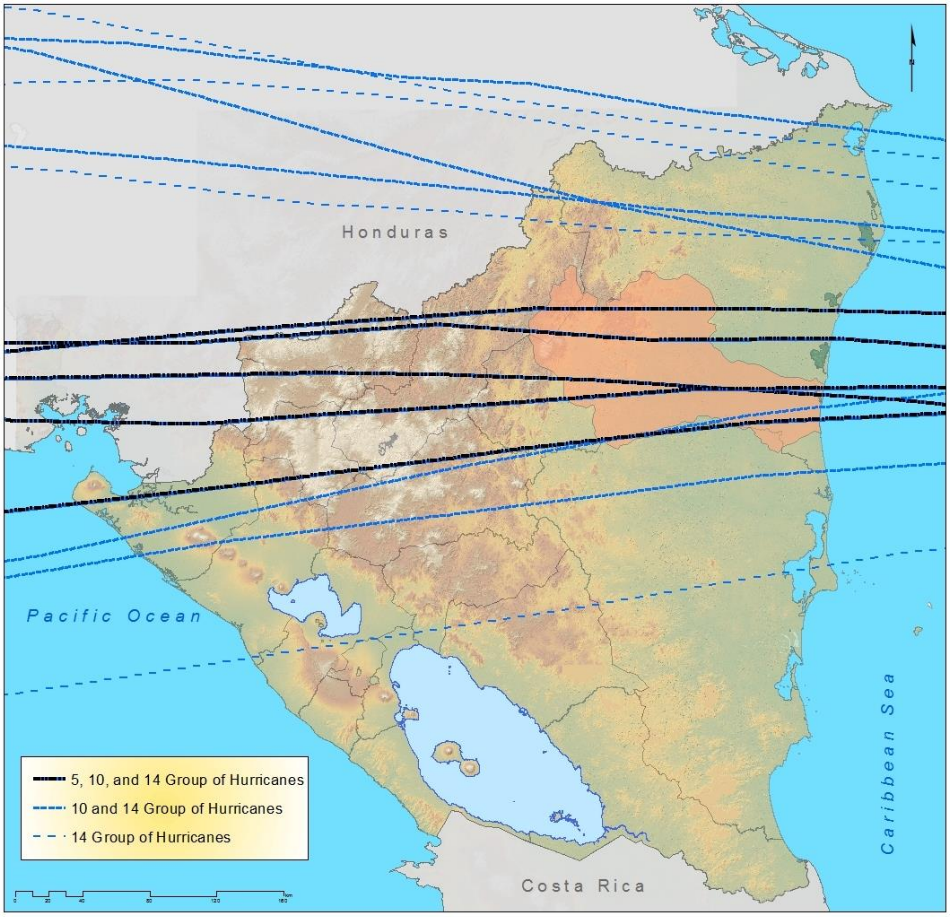


Figure 3.4. Map of synthetics hurricanes, which were divided into evaluation groups of five, ten, and fourteen hurricanes to assess the system performance of the forest optimization model (section 5.2.1).

CHAPTER 4

MODEL CALIBRATION AND DAMAGE PREDICTION

Previously generated the synthetic hurricanes, this section provides the steps to develop a data model calibration (DMC) and damage prediction model (DPM). This chapter brings a detailed description of calibration procedure and the subsequent prediction that is achieved in the study area (Figure 1.4 – 2). The DMC is implemented using Hurricane Felix track data (2007) and the DPM is developed, combined with synthetic hurricanes and DMC.

4.1 Data Model Calibration

Conceptually, in the forest literature, disturbances are defined as all possible sources that cause damage and mortality (Frelich 2002). Floods, storms, and wildfires are considered as natural disturbances mutually with physical agents (e.g., insect outbreaks, pathogen irruption) (Frelich 2002). Hurricanes are characterized by their wind speed, central pressure, and heavy rainfall. In this section, a data model calibration is stated and focuses on the adverse impacts (level of damages) of Hurricane Felix (section 2.4.1) within land cover classes (section 2.4.2). Precisely, it is implemented as a standard logistic regression model of damage rates for each land cover class (Inafor 2007) as response variable and both Felix track features and local vulnerability measures as explanatory variables. Realistically, if FOM deals with damage probabilities of hurricanes for the proposed land use classes, effectively every pixel has values between 0-1 (continuous variables), which represent a better environment for the FOM.

4.1.1 Generalized Linear Model

Damage ratings range from 0 to 1 (section 2.4.2). Therefore, a logistic regression specification is appropriate for the model calibration step and later for the damage predictions step (see section 4.3). The basic components of the standard logistic general linear model (logistic GLM) are:

1. The response variable is denoted by Y_i where the subscript $i \in \{1,2,\cdots N_j\}$ refers to a sample point of a given land cover class j and the set $\{1,2,\cdots N_j\}$ is the sampled area, for which the land cover j is feasible (Figure 2.8). The observations of the response variable are assumed to be statistically independent. Furthermore, the expected value of the response variable is μ_i, that is, $E(Y_i) = \mu_i$. In spatial analysis the expected value is conceptionally equivalent to the spatial trend.
2. The expectation μ_i is modeled, after being transformed by the monotonic *link* function $h(\cdot)$, through a linear combination of the explanatory variables, that is, $h(\mu_i) = \mathbf{x}_i^T \cdot \boldsymbol{\beta}$. The vector $\mathbf{x}_i$ denotes the set of explanatory variables at location i including an intercept term and $\boldsymbol{\beta}$ is the vector of unknown regression parameters. The symbol T in the exponent of a vector indicates a transposition operation.
3. The response variable Y_i follows a statistical distribution $f(\cdot)$ from the exponential family of distributions with the expected value μ_i and possible additional parameters, that is, $Y_i \sim f(\mu_i; additional\ parameters)$.

As a consequence of extrapolating the calibration model into the predicted area (Figure 2.1), the logistic regression is performed under the assumption of spatial independency. In the FOM, the spatial independency is explained from a Kriging interpolation perspective. In Kriging, an interpolation is performed based on a set of sample points that allows establishing a variogram function. At the range when the variogram reaches its sill, there is no remaining spatial dependence between the observations (i.e., no autocorrelation). Reaching the sill suggests that the covariance between the prediction points and the sample points beyond the range of the variogram no longer matters. To implement the calibration model, the spatial dependency can be ignored for the extrapolation, and only external information can be employed in the DPM. For instance, the calibration model residuals of land-cover BBF (Figure 4.1), provide evidence that we can ignore spatial dependence because the variogram estimated from these residuals reaches its sill rapidly (i.e., 0.0207861). Based upon Figure 4.2, it can be concluded that that past a range of ~ 5 km spatial autocorrelation can be ignored. Since the calibration area and the prediction area are more than 5 km apart, spatial autocorrelation cannot be utilized to improve the risk predictions in the prediction area.

4.1.2 Potential Damage Model

Section 3.1 (Figure 3.1) stated the nonlinear relationship between wind speed and distance from storm path. Consequently, to run a logistic regression, a potential damage model (PDM) for each land cover class (Eq. 1) has to be generated. The PDM is a multiplicative model based on the two most explanatory variables from a hurricane as wind speed at the center of the track and distance from the hurricane track. Considering the coriolis effect, the generated PDM also investigates the rate damage for the right and left side (Figure 3.1). This approach accepts

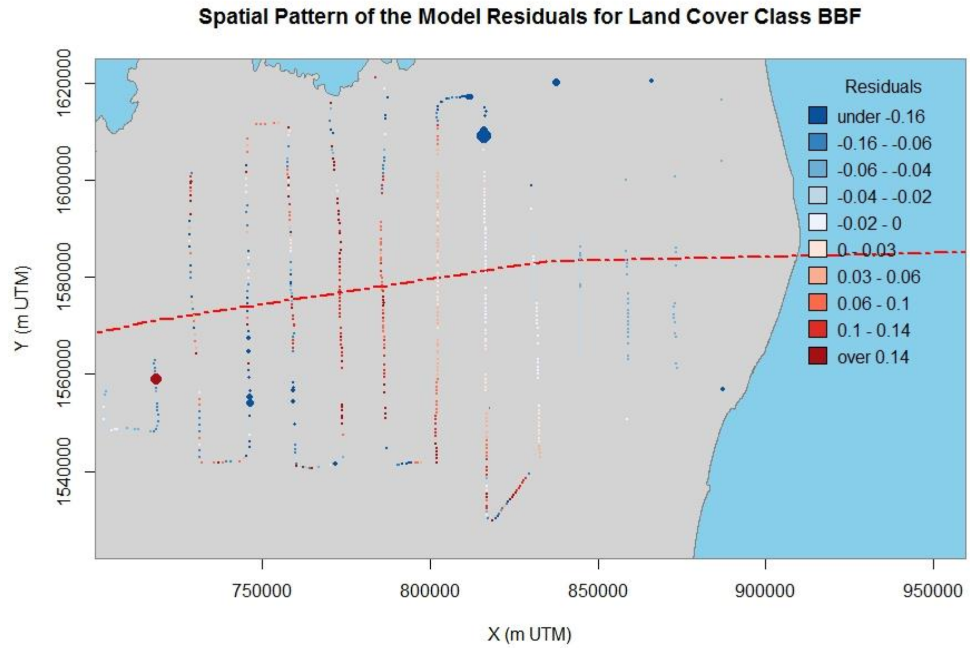


Figure 4.1. Spatial Pattern of the Model Residuals for Land Cover Class BBF.

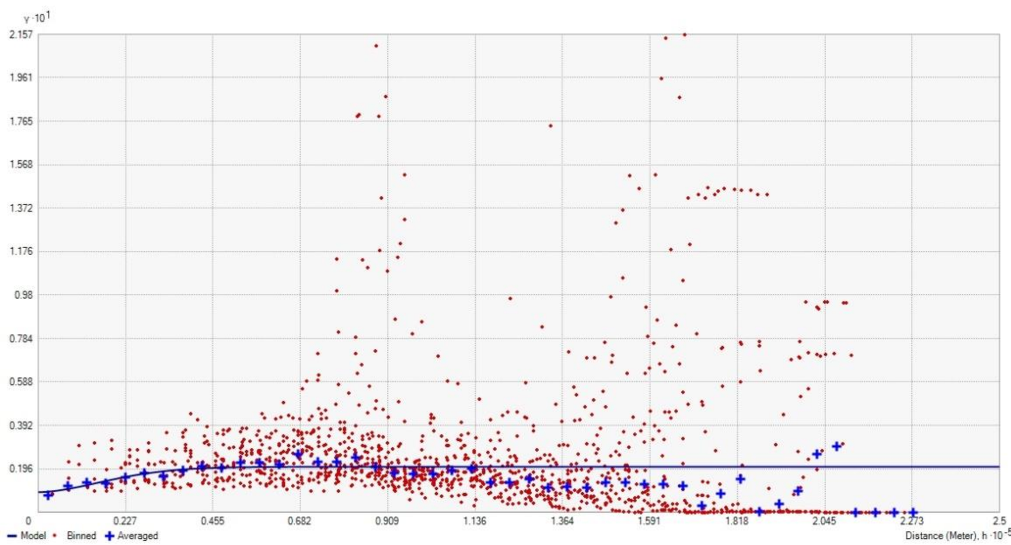


Figure 4.2. Variogram chart of the spatial pattern of the model residuals for land-cover class BBF.

the criticism that it is a very simplistic procedure, and further influential parameters, such as precipitation, speed of hurricane center over ground, can be summed. However, this information is challenging to obtain from Hurricane Felix or synthetic hurricanes. Therefore, a simple distance decay damage model in three parameters is assumed:

$$Pot_{Damage} = WindSpeed^{b_1} \cdot \exp\left(-\left(\frac{DistPath}{b_3}\right)^{b_2}\right) \qquad \text{Eq. 1}$$

where, Pot_{Damage} is the PDM, $WindSpeed$ is the wind speed of the hurricane in knots of Hurricane Felix, $b_1$is the power associated with wind speed (higher value suggests higher damage), $DistPath$ is the distance (km) from path of a hurricane, b_2 is the power of exponential function of distance from path (likelihood of distance from path), and b_3 is a scale of distance from the path.

Figure 4.3 clearly outlines how changing these parameters can influence the potential damage of a hurricane in the PDM. For instance, b_1 suggests that the damage of hurricane relates to wind speed is not a linear function. If b_1, which ranges from zero to one, is increased from 0.1 to 0.9, the potential damage factor increases (Figure 4.3, left plot). In addition, by changing b_2, which can range from zero to ten, the shape of the curve changes (Figure 4.3, right plot). Also, by changing b_3, the scaling factor or spread of the curve is modified. The interpretation of the scaling factor is on the curve of the Figure 4.4. If $b_2 = 2$ and $b_3 = 100$ (km), eighty-four percentage (area under the curve) of potential damage is occurring within 100 km from the center of the path.

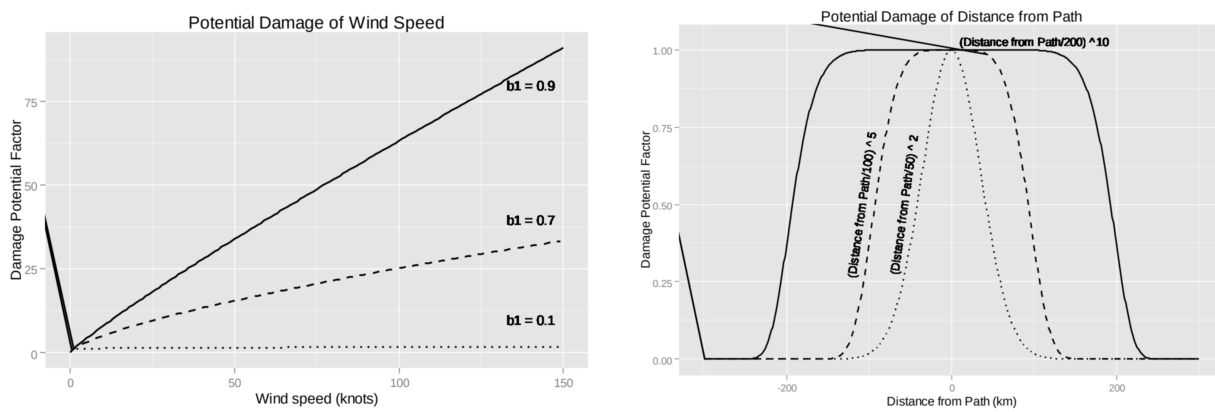


Figure 4.3. Plots of different theoretical values for b_1, b_2, and b_3.

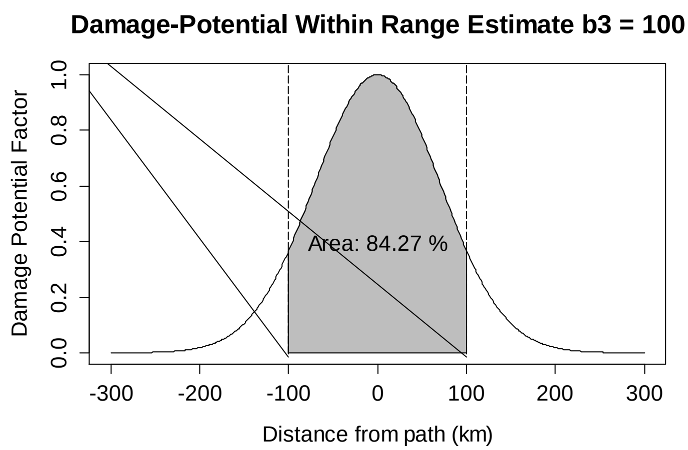


Figure 4.4. Integral graph calculating the percentage of Damage-Potential within range of estimate scale factor of $b_3 = 100$ ($b_2 = 2$). 84.27% of the damage is observed within $b_3 = 100$ distance from the center.

Since the functional form of the PDM is nonlinear and it cannot be model as simple linear logistic regression, a different approach has to be employed to obtain the parameters of Eq.1. Therefore, the PDM was solved using the grid search approach, which is a simple manner of optimization to achieve estimator parameters. The estimated parameters (b_1, b_2 and b_3 of Eq. 1) are obtained by employing a GLM function (*logit link*) setting the damage rate as the response variable and PDM as explanatory variables. Later, the maximum likelihood of all possible combinations are compared to one another, and the highest maximum likelihood determines the optimal set of parameters. As an illustration of grid search, the diagram of Figure 4.5 started with an estimated coarse grid ($b_1 = 0 - 3$ in increments of 1, $b_2 = 1 - 10$ in increments of 1, and $b_3 = 10 - 150$ in increments of 10), and the first coarse range of the parameter values are acquired ($b_1 = 0 - 1$, $b_2 = 2 - 4$ and $b_3 = 100 - 120$). A new grid is then created based on the previous grid search and finer grid is employed to increase the precision (for example the zoom in 1 of Figure 4.5, $b_1 = 0.0 - 1.0$ in increments of 0.1, $b_2 = 2 - 4$ in increments of 0.2 and $b_3 = 90 - 130$ in increments of 5). The grid search moves to finer grids with more precision until the parameters are the same with more precision in the grid. Finally, this method is completed for the pooled observations (total of 955 observations in Table 2.3).

4.1.3 Additional Explanatory Variables

Besides the PDM, local factors (Figure 3.1 and Table 4.1), which are potentially related to the destructive power of Felix, were tested as explanatory variables. These variables are local vulnerability measures (such as elevation, slope, and aspect) and hurricane specific variables (such as pressure and distance from landfall). Also, the right-hand and left-hand sides along the hurricane path are evaluated (Figure 3.1). Here, it is assumed the hypothesis that damage rates depend on the type of land cover, wind speed, and other local factors. Therefore, several standard logistic regressions are assessed for each land cover class with varying sets of explanatory variables. For instance, greater hurricane damage is expected at higher slope and east aspect (45–

135 degrees) and while less severe hurricane damage is expected at higher elevation. Following the model (each model is land cover class-specific) that is tested:

$$rate\ damage_{LuC} = f(PDM, topography, pressure, distances)$$

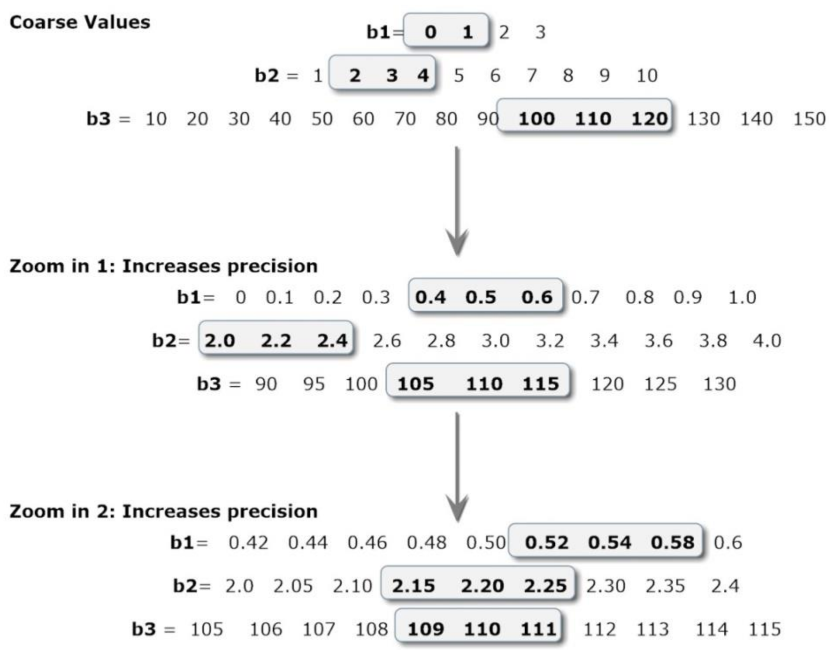


Figure 4.5. Initial coarse values and two steps zoom in the estimated values of parameters for the Potential Damage Model applying a grid search method.

Table 4.1. Explanatory variables tested in the logistic regression.

Variable Name	Values	Units	Description
wind speed	50-147	kt	Wind speed of the report Tropical cyclone report: Hurricane Felix (Beven 2008)
distance from path	0- 209	km	Distance in km from path of Hurricane Felix
pressure	934-980	mb	Pressure of the report Tropical cyclone report: Hurricane Felix (Beven 2008)
distance from landfall	0-51	km	Distance in km from landfall of Hurricane Felix
RL	1 or 2	--	Side of the Path, Right = 1, Left = 2
elevation	0-743	m	Elevation over sea level from the DEM
slope	0-100	%	Slope (%) generated from DEM
Aspect	0-360	degree	Aspect generated from DEM

4.2 Results of Data Model Calibration

The optimal parameters for the Felix damage rate are determined by logistic regression. Table 4.2 portrays the estimated parameters for the PDM of pooled and individual land use classes PDM. In addition, to account for the coriolis force, the PDM was tested with the observations of left and right side of Hurricane Felix path. It is expected that higher damage potential exists on the right side of the hurricane due to the counterclockwise rotation in the northern hemisphere (Figure 3.1).

Table 4.2. Estimated parameters of b_1, b_2 and b_3, for pooled model and individual land use classes after the implementation of GLM on grid search method.

Model	PDM	Obs	b_1	b_2	b_3
PDM-Pooled	Pooled PDM, four land use classes	955	0.57	2.20	110
PDM-BBF	Dense Broadleaf Forest	665	0.69	2.03	110
PDM-OBL	Open Broadleaf and Mixed Forest	134	0.69	2.30	112
PDM-FFW	Forest fallow	101	0.18	2.99	106
PDM-PIN	Pine	55	0.18	2.00	92

Table 4.3. Estimated parameters of PDM for left and right hand side observations (coriolis force) of Hurricane Felix.

Model	PDM	Obs	b_1	b_2	b_3
PDM-Pooled	Pooled PDM	955	0.57	2.20	110
PDM-Right	Pooled PDM for right side	572	0.40	2.20	120
PDM-Left	Pooled PDM for left side	383	0.50	2.10	74

The estimated parameters for both pooled and land cover specific models (Table 4.2) suggest similarly in calculated values among all classes. For instance, the parameter b_1, for particular landuse class models, the estimated parameters are on average of 0.44, which is a similar value to the estimated parameter for the pooled model. In Table 4.2, because the canopy structure provides less resistance to hurricane winds, b_1 is substantially smaller in the forest fallow and pine land covers (0.18). Also, the estimated average value of the estimated parameter b_2 for individuals landuse is similar to the pooled model (i.e., average value of 2.33 compared with pooled value of 2.20). Investigating the coriolis effect, while the scale of distance from the path (b_3) is greater on the right-hand side (Table 4.3), the wind speed component (b_1) is unexpectedly lower. The prior results are inconclusive and imply that the inadequacy of the collected data after Hurricane Felix do not allow discrimination of the coriolis effect (either side of the hurricane). This deficiency of the forest damage assessment does not provide representative sample of the different land-covers in the right side or the left side. Consequently, the PDM with a single pooled model (Eq. 2) was implemented for all landuse classes:

$$Pot_{Damage} = WindSpeed^{0.57} \cdot \exp\left(-\left(\frac{DistPath}{110}\right)^{2.2}\right) \quad \text{Eq. 2}$$

The pooled PDM, which represents the baseline damage level, independent of landuse class, is applied to DMP of individual landuse classes (Eq. 2). First, although the power of the wind speed was expected to be higher, the value of b_1(Figure 4.6-a) resulted in low value. Second, unexpectedly, the power of the exponential function of distance decay suggests an approximate shape of a normal distribution with a value of $b_2$equal to 2.2 (Figure 4.6-b). Third, the scale of distance to path (b_3 = 110) is close to the practically average distance from the path (80 km) of a hurricane, according to the NOAA's National Hurricane Center. The average extension of a hurricane eye can be extended up to 200 km wide in both directions with an average of 80 km (National Center for Atmospheric Research 2013). In Figure 4.7, the percentage of damage based on this scale factor is 86%. Finally, the PDM of Hurricane Felix

(Figure 4.8), which represents the nonlinear PDM, is conceptually right, as expected. It can be observed the highest possible damage close to both the coastline and track. Conversely, the lowest potential damages are located far from the track and from the coastline.

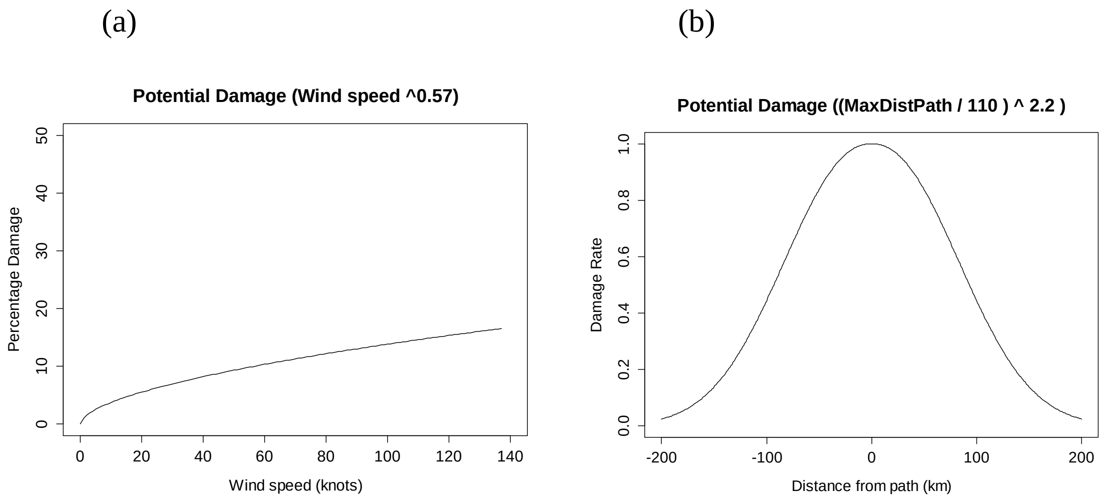


Figure 4.6. Plot of the estimated parameters of the Pooled PDM. The left figure portrays how the percentage of damage increases with the wind speed. The right figure shows the distance from the path decay function.

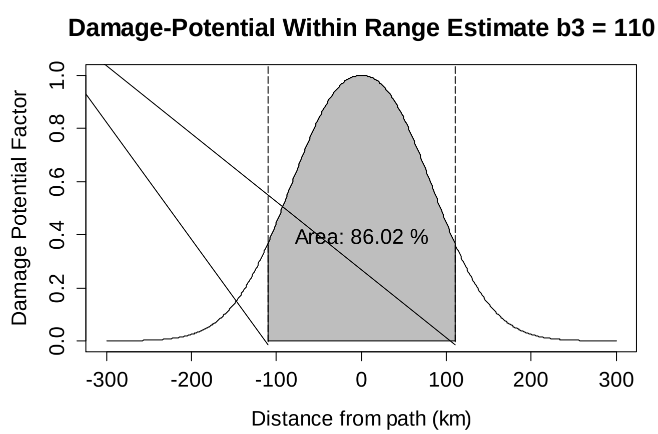


Figure 4.7. Percentage of damage (86.02%) under the curve for the parameters b_2 = 2.2 and $b_3 = 110$ km.

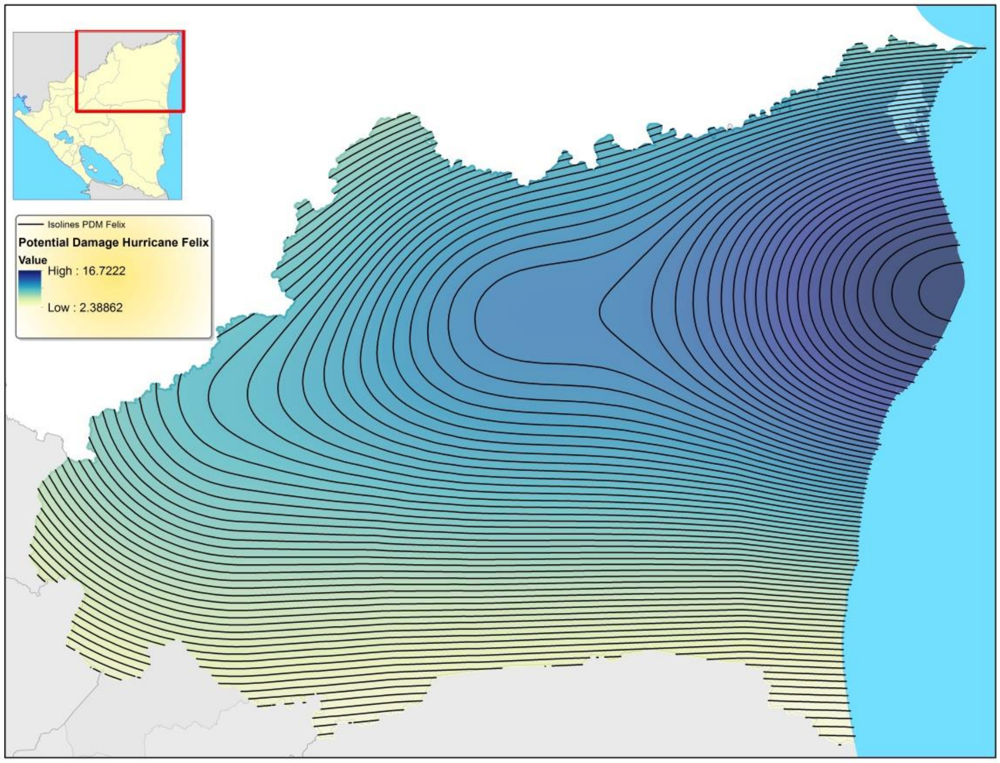


Figure 4.8. Potential Damage Model of Hurricane Felix (2007) in RAAN area and the prediction area of Prinzapolka River, eastern Nicaragua.

Formerly, the PDM was determined and considered as explanatory variable; the next step is to include other explanatory variables (section 4.1.3) in the GLM. In the first step of the model calibration, each land cover class is modeled with the standard GLM approach. Then, each explanatory variable is evaluated on whether it is capable of significantly explaining the variation in the response variable. The DMC for each land cover class is shown in the Table 4.4. Each model belongs to each land cover class and its explanatory variables. In this analysis, the explanatory variable distance from coastline and pressure were not statistically significant in the logistic regression model due to these explanatory variables are high correlated with wind speed of hurricanes. This result supports the findings by Stanturf et al. (2007) who concludes that the risk of hurricane damages is a function of distance from the coastline.

Table 4.4. Logistic regression models for each land uses clauses. For forest fallow and pine land cover classes, elevation (β_2) and slope (β_3) are not significant.

Variable	Dense Broadleaf Forest (BBF - model)		Open Broadleaf and Mixed Forest (OBL – model)		Forest fallow (FFW - model)		Pine (PIN - model)	
Observations	665		134		101		55	
	Coef	*p-value*	Coef	*p-value*	Coef	*p-value*	Coef	*p-value*
β_0, constant	-9.1224	*0.000*	-7.0133	*0.0036*	-9.931	*0.0008*	-5.9867	*0.126*
β_1, PDM	0.8556	*0.000*	0.6566	*0.0005*	0.881	*0.0002*	0.4240	*0.123*
β_2, Elevation	-0.0050	*0.000*	-0.0034	*0.0306*	--	--	--	--
β_3, Slope (%)	0.0351	*0.081*	--	--	--	--	--	--

It is important to notice; the PDM (β_1) is statistically significant to the four logistic regression models. As was mentioned above, wind speed and distance from the path were crucial to predict damage by hurricanes. The intercept coefficient (β_0) (Table 4.4) for each land cover class suggests that PIN is the most resilient landuse class (lowest susceptibility), lower values of β_0 represents more hurricane damage. The second more resilient landuse class is OBL. The BBF – model (less resilient land cover class) included elevation (β_2) and the slope (β_3) as two additional local explanatory variables. Presumably, the small sample size of PIN – model land cover can explain the bottom-line significant p-values of β_0 and β_1. For the models of FFW and PIN, elevation and slope are not significant.

The elevation (β_2), as explanatory variable, become significant for both BBF – model and OBL – model (two land cover with more observations). According to these findings, in the eastern Nicaragua, hurricanes become less harmful once hurricanes are approaching mountains. Furthermore, as the slope (β_3) increases, the risk of hurricane damage increases for the BBF and

OBL landuse classes. Zimmerman et al. (1994, 911-922) found that uprooting is the most common damage on higher slopes. In contrast, the reason neither elevation (β_2) nor slope (β_3) is meaningful explanatory variables for PIN is this landuse class is placed in the flatland of eastern Nicaragua (Figure 2.8). To measure the validity of the results generated by the models, a quality control was exercised for the land cover classes. For instance, the comparison of observed and predicted damage rate for the BBF – model is presented in Figure 4.9. This suggests an acceptable model, the blue line of Figure 4.9 (a) is the line of BBF-model and the red line a perfectly predicting model. Also, Figure 4.9 (b) depicts a comparison damage rates and residuals of BBF-model. Based upon these figures, it can be concluded that the estimated model can be utilized for damage risk prediction.

(a) (b)

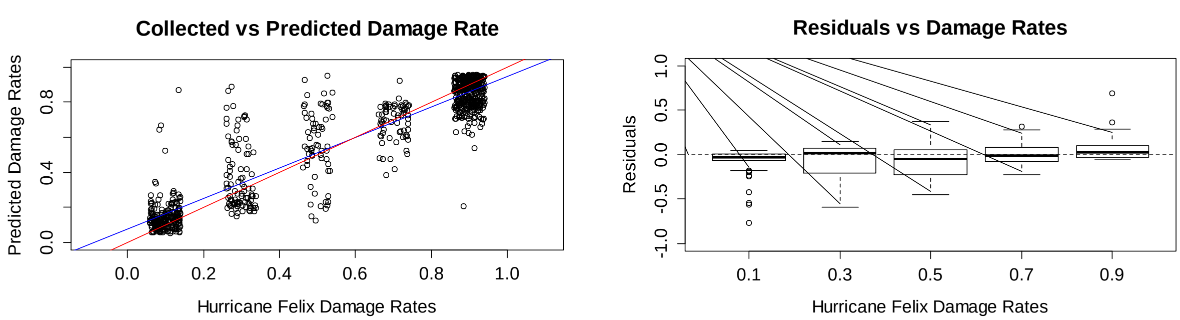


Figure 4.9. Quality control graph by comparing observed damage rate of Hurricane Felix and predicted damage rate using DPM. (a) Plot of measured damage rates and predicted damage rates for land cover BBF. (b) Boxplot of measured damage rates and residuals after applying the Data Prediction Model for land cover BBF.

4.3 Damage Prediction Model

Based upon the DMC presented previously, the aim of DPM was to predict the potential damage of the synthetic hurricanes developed by Emanuel et al. (2006) as input for each possible hurricane in the future time (section 3.2). To obtain probabilities of damage, a prediction model has been performed. The results are four models (one for each landuse class) predicting the damage risk (on a scale of 0-1) for each land cover class, given the path and strength of the synthetic hurricanes (section 3.2). The output of the DPM (fourteen hurricanes), represent the map risks that are input for the forest optimization model (FOM) (Figure 1.4). The DPM was applied to the entire RAAN department and then clipped to the feasible growth area of the class in the prediction area (Prinzapolka river watershed for each synthetic hurricane). For instance, Figure 4.10 portrays the PDM for the synthetic hurricane track 099 (Table 3.1). Also, the DPM generates one raster layer for each land cover class for each synthetic hurricane. It is expected that the DPM helps land managers and institutions to understand the severity of damages caused by hurricanes and the local factors that are related to those damages. The author expects that land managers implement the forest activities, which are more resilient to damages posed by hurricanes.

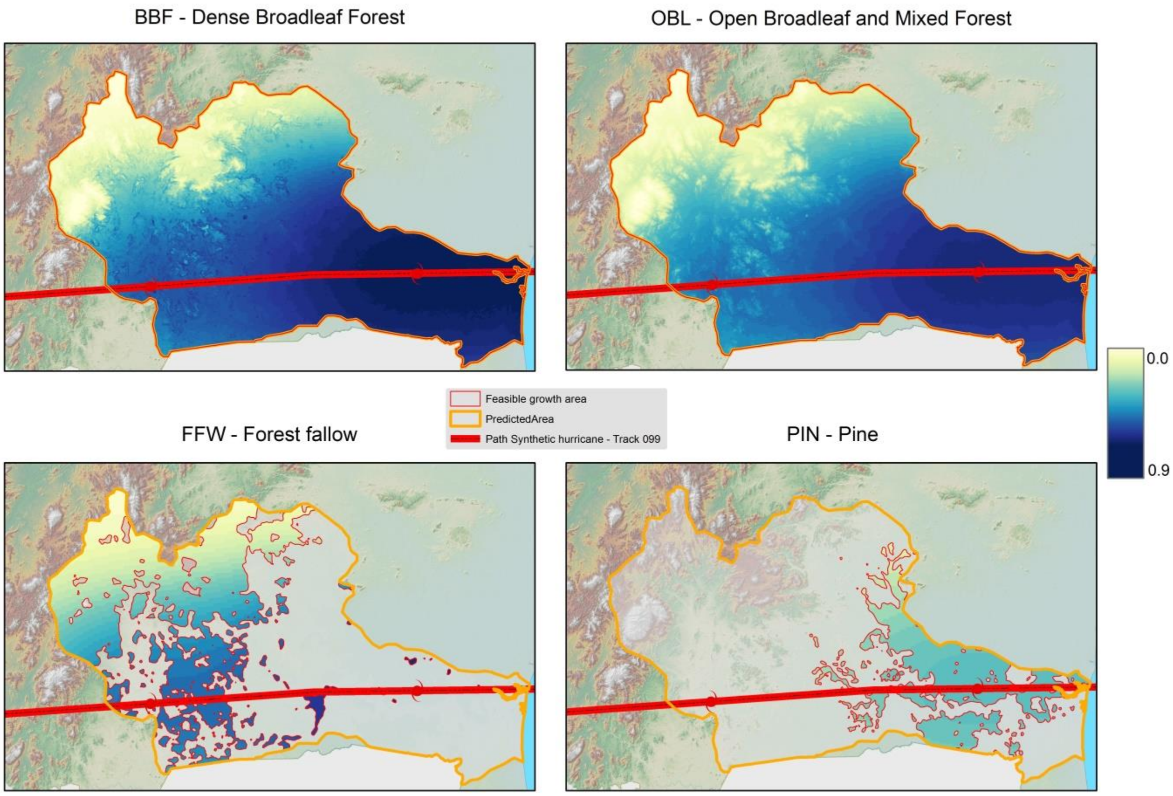


Figure 4.10. Implementing DMC (predicted damage probabilities, 0-1) in the predicted area (Prinzapolka river watershed) for each landuse class, using the synthetic hurricane track number 099.

CHAPTER 5

FOREST OPTIMIZATION MODEL

This chapter describes the forest optimization model (FOM), which is a deterministic mathematical optimization model. The results of implementing the FOM in eastern Nicaragua are also presented in this chapter. The FOM is expected to produce a land management allocation solution that optimizes land use management (as measured by reduction of predicted damage inflicted by future hurricanes) subject to different sets of constraints (i.e., adjacency, budget, minimum and maximum areas).

5.1 Forest Optimization Model

Spatial optimization problems in general consist of three components: an objective being sought, decisions to be made, and constraining conditions. The objective relates to the purpose of the problem, often reflecting goals to be achieved, such as minimizing risks or maximizing benefits. The objective is often structured using one or multiple mathematical objective functions. In the mathematical context of the FOM, the decisions to be made are determined by the values assigned to various decision variables (Tong and Murray 2012, 1290-1309). Constraining conditions represent sets of conditions that limit the possible values that the decision variables can assume. In any spatial optimization problem, constraints can be applied throughout the study area (global constraints) a sub region of the area (e.g., a municipality or watershed) (regional constraints); or in a pixel or management unit (local constraints). The flowchart shown in Figure 5.1 depicts the main steps involved in implementing the FOM.

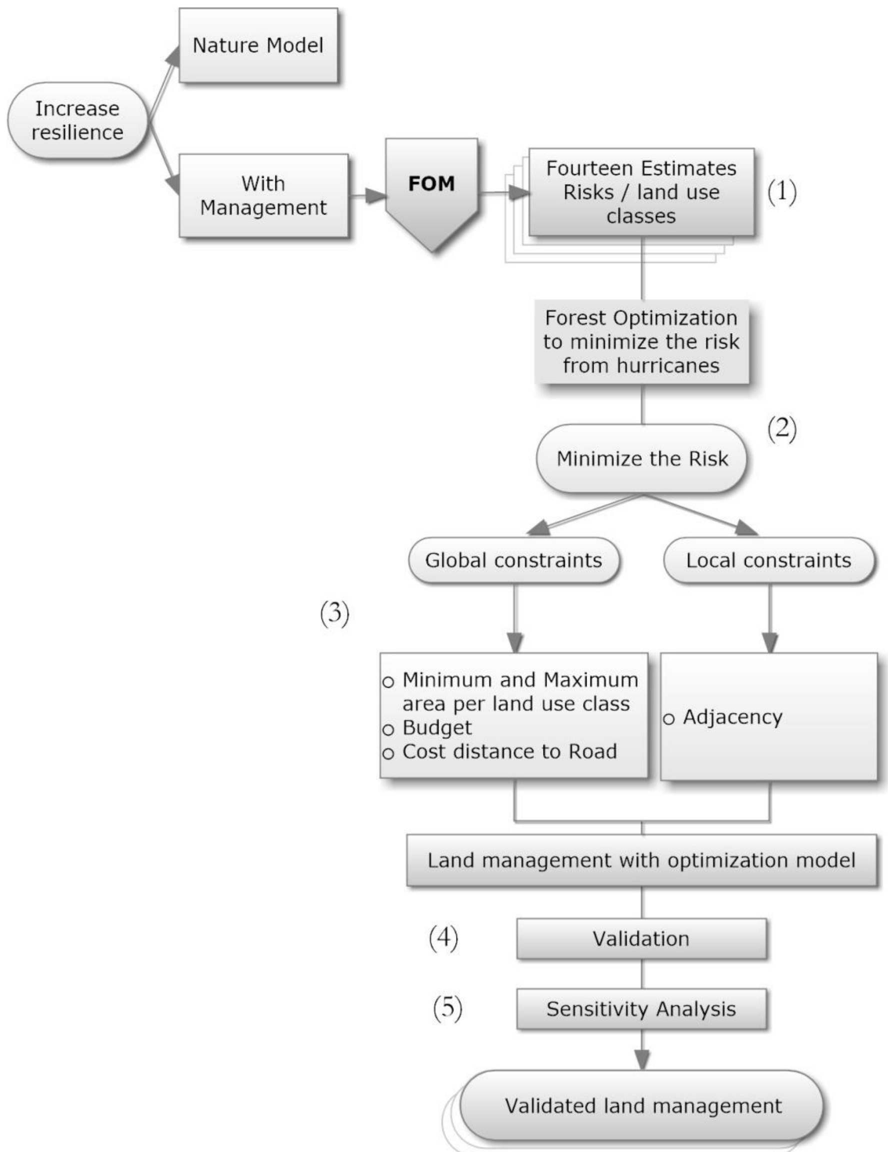


Figure 5.1. Flow chart portraying the analysis to be performed in the Forest Optimization Model (FOM). (1) The fourteen synthetic hurricanes obtained from Emanuel et al. (2006), (2) The objective function is defined, (3) the global and local constraints are reviewed, (4) a validation is implemented, and (5) sensitivity analysis is evaluated.

5.1.1 Modifiable Area Unit problem – MAUP

In any spatial analysis, the geographic scale of the analysis has to be considered. Landform, vegetation, and soils data may be measured at a variety of spatial scales, and are often modeled at a much coarser resolution than their true natural variability (Young et al. 2004, 17-77). Models can produce different results depending on how the study area is partitioned for analysis. This phenomenon is termed the Modifiable Area Unit Problem (MAUP). What is the effect of MAUP on modeling hurricanes and implementing land management activities in eastern Nicaragua? In this study, we are dealing with phenomenon on a large scale (e.g., implementing forest activities) and others on a relatively small scale (e.g., hurricane trajectory models with genesis of 0.5º x 0.5º longitude -latitude that is ~ 50 km x 50 km scale raster resolution). The MAUP cautions us to question how this particular scaling of the data will impact the results of this study's analysis. Perhaps the best method of investigating the impacts of the MAUP is to conduct identical analyses at different scales and compare the resulting differences. However, this type of evaluation was not conducted in the present study and remains open for future researchers.

5.1.2 Objective function

In this research, the objective is to minimize the impacts of hurricanes over the study area by determining the pattern of land uses that is most resilient to storm damage (Figure 5.1, step 1). Hurricane damages were estimated using a damage prediction model that is dependent upon landuses, hurricanes tracks and storm intensities (section 4.1 and Figure 4.8). Therefore, the decision variables used in this optimization model represent landuses, and the objective function represents the risks produced by any given pattern of landuse. The optimization model searches for a pattern of landuses that minimizes risks (Eq. 3).

$$\sum_{h=1}^{H} \cdot \sum_{k=1}^{L} \cdot \sum_{i=1}^{r} \cdot \sum_{j=1}^{c} D_{ijk} * R_{ijkh} \qquad \text{Eq. 3}$$

where i is the number of rows, j is the number of columns, k is the number of landuses, and h is the number of potential damage from synthetic hurricanes. D_{ijk} is the binary decision variable representing landuse class k for raster cell i, j. The return values, R_{ijkh}, represent the risk of hurricane damage realized when cell i, j is assigned to landuse k (DPM, section 4.3).

5.1.3 Constraints

Constraints establish necessary conditions that must be satisfied in order for a solution (i.e., a set of values assigned to the decision variables) to reflect a realistic possible pattern of and uses. The following subsections describe the constraints implemented in the FOM:

Binary variable constraint

One and only one landuse class must be assigned to each pixel. This means that the sum of all of the decision variables that reference a single pixel must be 1 (Eq. 4).

$$\sum_{k=1}^{L} D_{ijk} = 1 \qquad \forall_k \qquad \text{Eq. 4}$$

where D_{ijk} is the binary decision variables assigned to landuse class k for i, j for all combination of landuse class.

Adjacency constraint

The FOM also addresses the compactness of the forest activities in an effort to prevent incompatible land uses from falling into management units adjacent to one another, to prevent an overly large contiguous area from being assigned to a single land use, and to reflect economies of scale. Currently, the use of adjacency constraints is standard practice in the management of public and private forests (Murray and Weintraub 2002, 779-789). Adjacency can be thought of as the nominal, or binary, equivalent of distance. Two spatial entities are either adjacent or they are not. There are many ways that we can apply adjacency to a set of data, the most obvious and simple case being a set of pixels, in which we consider any two pixels that share an edge to be adjacent (O'sullivan and Unwin 2010). In this study, the details of how adjacency constraint is formulated (including four neighbor cells) are presented in Eq. 5.

$$D_{ijk} \leq D_{i+1,j,k} + D_{i-1,j,k} + D_{i,j+1,k} + D_{i,j-1,k} \qquad \forall_{ijk} \qquad \text{Eq. 5}$$

where D_{ijk} is the binary decision variables assigned to landuse class k for i, j, $D_{i+1,j,k}$ is the right neighbor cell, $D_{i-1,j,k}$ is the left neighbor cell, $D_{i,j+1,k}$ is the upper neighbor cell, and $D_{i,j-1,k}$ is the lower neighbor cell. This formulation proposes that if one cell is assigned to a landuse class k, at least one adjacent cell must also be assigned to the same landuse class k for all of all combination of landuse class.

Minimum and maximum area constraints

Area limits for each landuse (minimum and maximum area for each landuse) is another constraint. Due to the problems associated with monocultures (Grimm, Schmidt, and Wissel 1992, 143-161; Gibson and Jones 1977, p. 139-161), it is not recommended for single landuses to be applied over large contiguous areas. Therefore, area constraints are required for minimum area (Eq. 6) and maximum area (Eq. 7).

$$\sum_{i=1}^{r} \cdot \sum_{j=1}^{c} D_{ijk} \geq min_{ij} \qquad \forall_k \qquad \text{Eq. 6}$$

$$\sum_{i=1}^{r} \cdot \sum_{j=1}^{c} D_{ijk} \leq max_{ij} \qquad \forall_k \qquad \text{Eq. 7}$$

where min_{ij} is the minimum number of area unit (ha) to be assigned to i, j for each landuse class k and max_{ij} is the maximum number of area unit (ha) to be assigned to i, j for each landuse class k. This formulation proposes that a user can define some minimum or maximum area for each landuse class k to spatially optimize the study area.

Budget constraint

In Nicaragua, a developing country, most implemented land management activities are based upon available budget. Funds come not only from the government (national and regional government) but also from international aid organizations (e.g., German Agency for International Cooperation - GIZ, Organization of American States - OAS, Spanish Agency for International Cooperation and Development, Taiwanese and Chinese cooperation, among others). In the model developed here, the sum of operative cost C_{ijk} to implement the landuse class k has to be less or equal than a predefined budget (M) for all combination of landuse classes. The operative cost is very complex and can be referred as implementation cost, maintenance cost, or conversion land-cover cost. Since these costs involve temporal problem and our model does not considered the temporal aspect, this model is ignoring these types of dynamically costs and considering a fix number of implementation cost. In this way, the FOM maximizes the total amount of available money (Eq. 8).

$$\sum_{i=1}^{r} \cdot \sum_{j=1}^{c} \cdot \sum_{k=1}^{L} C_{ijk} - M \leq 0 \qquad \forall_{ijk} \qquad \text{Eq. 8}$$

The objective function, the decision variables, and constraints are solved using LINGO, which is a commercial optimization package. Two source codes (written in VB.NET) were developed to automatize the procedure of implementing the FOM. The purpose of the first code (ArcToLingo_FOM) (Figure 5.2) is to read the cell-by-cell raster damage ratings from the fourteen synthetic hurricanes (DPM of section 4.3) and formulate the mathematical equations that comprise the objective function and constraints of the FOM. These equations are written to an ASCII file suitable for import into LINGO. Likewise, the second code (LingoToArc_FOM) reads LINGO's output containing the optimization solution (text file) and converts it into a raster data format native to ESRI (ESRI 2008). The two codes developed by the author are available upon request.

5.2 Results of Forest Optimization Model

The results of implementing the FOM in Eastern Nicaragua are presented in this section. The FOM is expected to both optimize land use management (as measured by reduction of predicted damage to be inflicted by future hurricanes) based on different sets of constraints (i.e., adjacency, budget, minimum and maximum areas) and also to produce land management allocation solution.

5.2.1 System Performance

To assess the performance of the optimization model in terms of computational efficiency, the synthetic hurricanes (Emanuel et al. 2006, 299-314) were divided into evaluation

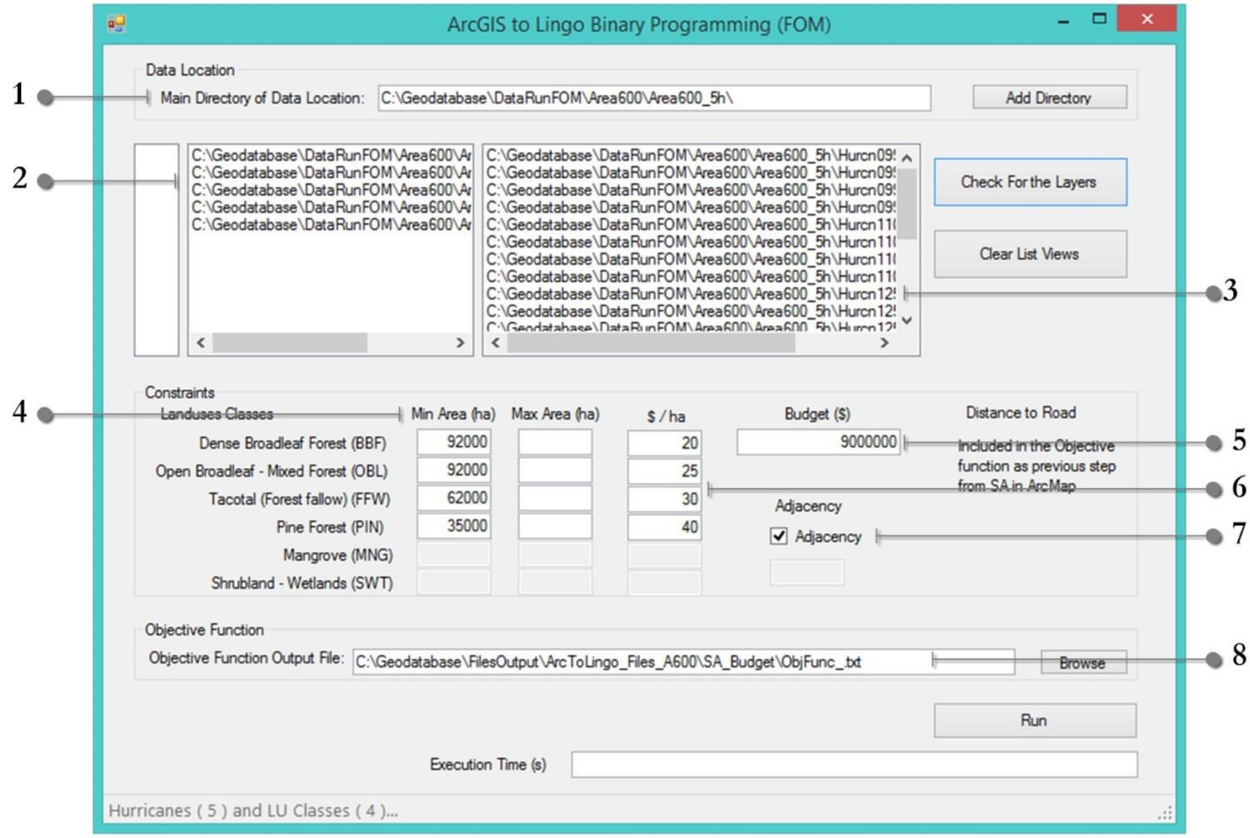


Figure 5.2. The interface written in VB.NET to automatize the procedure of implementing the FOM in LINGO software package. In this interface, a user can customize (1) the folder where the potential damages are located, (2) number of hurricanes to be in the FOM (e.g., five hurricanes), (3) four landuse classes per each synthetic hurricane, (4) minimum and maximum are constraints (ha), (5) budget constraint ($), (6) implementation cost ($/ha) of landuse classes, (7) adjacency constraint, and (8) output ASCII file.

groups of five, ten, and fourteen hurricanes (Figure 3.4). Given the form of the model, the number of decision variables increases proportionally to the number of hurricanes being evaluated. Thus, it stands to reason that model performance is dependent on the number of hurricanes. The main criteria used to derive the three evaluation groups were (1) intensity of the storms (low, medium, high), and (2) distance of the storm's path from the Prinzapolka river watershed. The execution time needed to run the model with each of these three groups on databases containing various numbers of raster cells are shown in Figure 5.3.

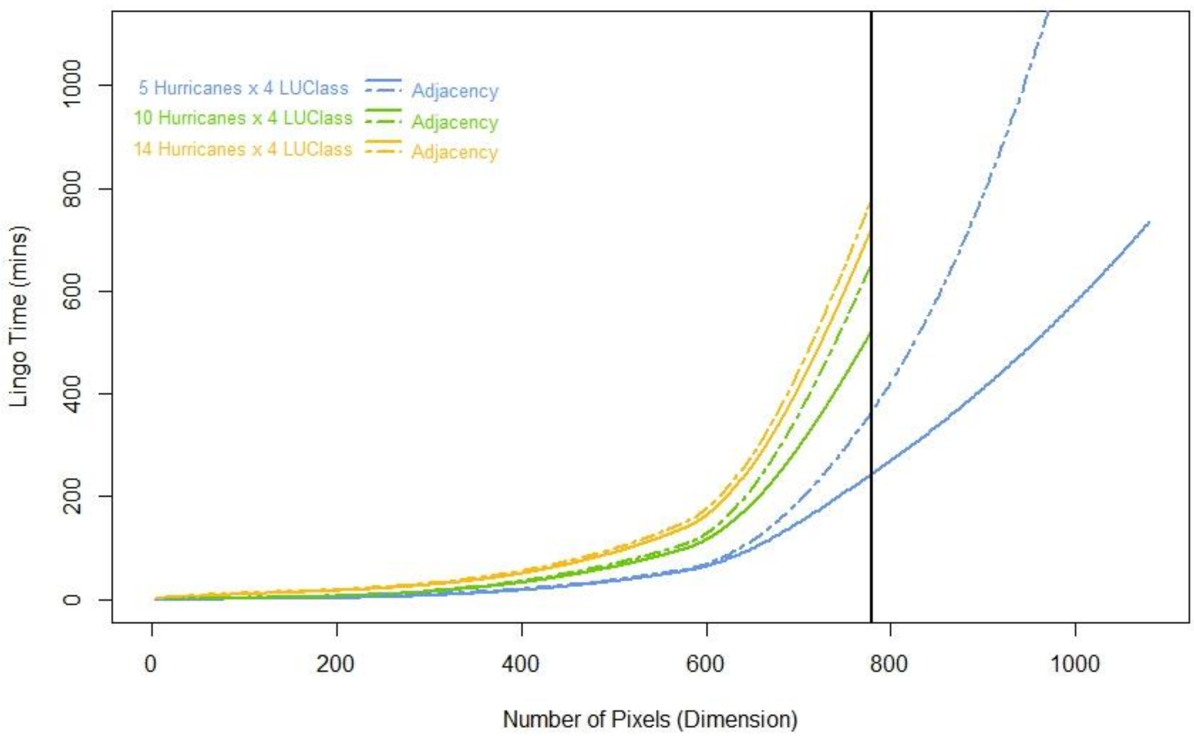


Figure 5.3. System performance (dimension of number of pixels vs time solution in LINGO) of the Forest Optimization Model implemented a different set of hurricanes (5, 10, and 14) with and without adjacency constraint.

The results from Figure 5.3 indicate that system performance of the FOM is influenced by three parameters: (1) the number of hurricanes being evaluated, (2) the presence/absence of adjacency constraints, and (3) the number of pixels in the analysis area. By changing these parameters, the extent of a model that can be solved in a manageable time can be estimated. For instance, a scenario with a data set of 1000 x 1000 pixels, five hurricanes, and no adjacency constraints (~ five million decision variables) can be solved in approximately ten hours.

It is important to note that even the smallest of models evaluated in Figure 5.3 involved tens of thousands of variables and similar numbers of constraints, yet solutions were obtained for all but the largest models in reasonable timeframes. The reason for this model efficiency lies in the nature of the model variables. With all decision variables being binary, the result is a perfect branch and bound scenario where every single decision has two branches. These two branches are not only symmetric but also linear.

The results shown in Figure 5.3 also show a clear inflection point. This represents the limits of the computer's memory; problems of a size larger than the inflection point exceed the computer's memory capacity and therefore require the machine to shuffle information back and forth between memory and hard disk. Since disk access is very slow relative to memory access, models that require disk storage require much more solution time than do smaller models.

5.2.2 Natural System Performance

Due to the performance issues just discussed, the study area was limited to a raster layer of 624 x 595 pixels covering an area of approximately three thousand square kilometers (pixel size of 90-by-90 meters) (Figure 5.4) and using the group of five hurricanes. This region contains areas where each landuse class can be implemented. The BBF and OBL land use classes are feasible throughout the entire study area, while classes FFW and PIN are possible in 26 and 17 percent of the area, respectively (Figure 5.5). This ability to support all of the possible landuses makes the reduced study area a viable test site. This section describes how the adjacency, minimum and maximum area, and budget constraints influence the management plans produced by the FOM for this study area.

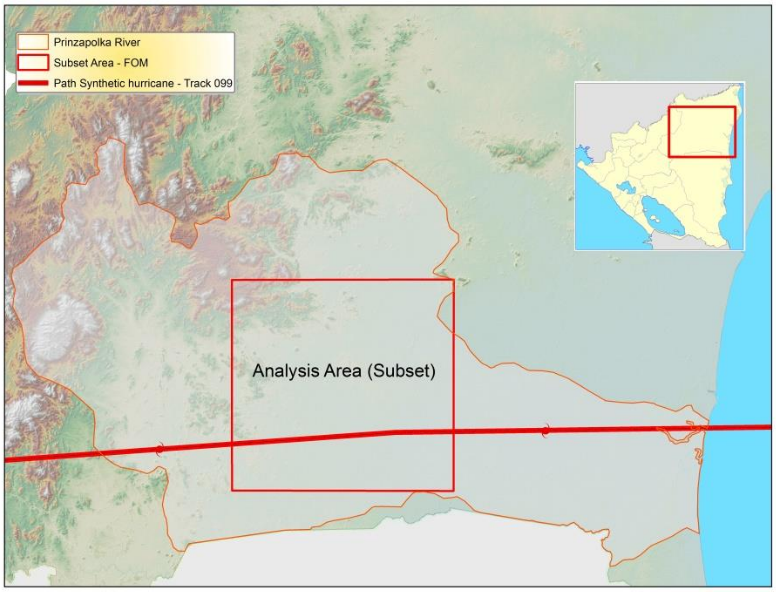


Figure 5.4. Map portraying the analysis area (subset area) in relation to the original study area (Prinzapolka River).

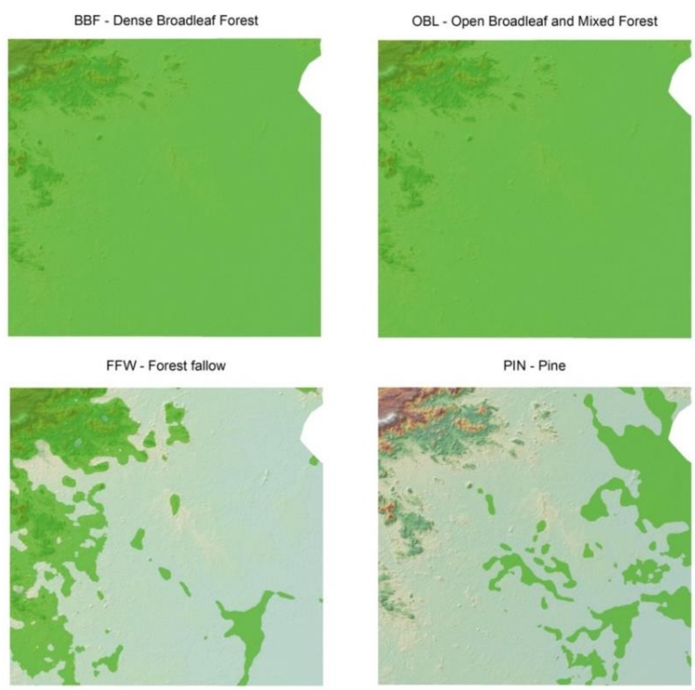


Figure 5.5. Feasible growth areas for four landuses classes in the subset area to implement the FOM.

5.2.2.1 Validation

The main purpose of this section is to test the plausibility of the FOM by exploring the solution space using extreme values of the constraints. Models were evaluated using unrealistically severe area constraints, tight budgets, and extreme costs per hectares of land use. The goal was to force the model to produce predictably extreme results. The model's outputs confirm that the FOM is producing intuitively expected results in each extreme case. This indirectly supports the idea that model can be trusted to produce plausible results in less extreme cases, and therefore supports the validity of the model.

The following subsections describe and compare these extreme models used for validation purposes.

<u>Adjacency</u>

The use of Adjacency Constraints is standard practice in the management of public and private forests (Goycoolea et al. 2005, 490-500). Consequently, the FOM is designed with the capability of including adjacency constraints. Models that omit adjacency constraints can be expected to produce a salt- and- pepper effect (a result of assigning isolated pixels to land uses different from that of all their neighbors) and to produce a better result in term of total value of the objective function (because individual cells can be assigned to their most beneficial land use without regard for the land uses assigned to their neighbors). Conversely, including adjacency constraints will remove the salt-and-pepper effect and will make the value of objective function less optimal.

Figure 5.6 shows that adjacency constraints had precisely the expected results on the FOM. Furthermore, the FOM results presented on the left of Figure 5.6 (without adjacency constraints) produced an objective function value of 1,206,014,000 while those on the right (with adjacency constraints) produced an objective function value of 1,206,027,000 – again, exactly as was expected.

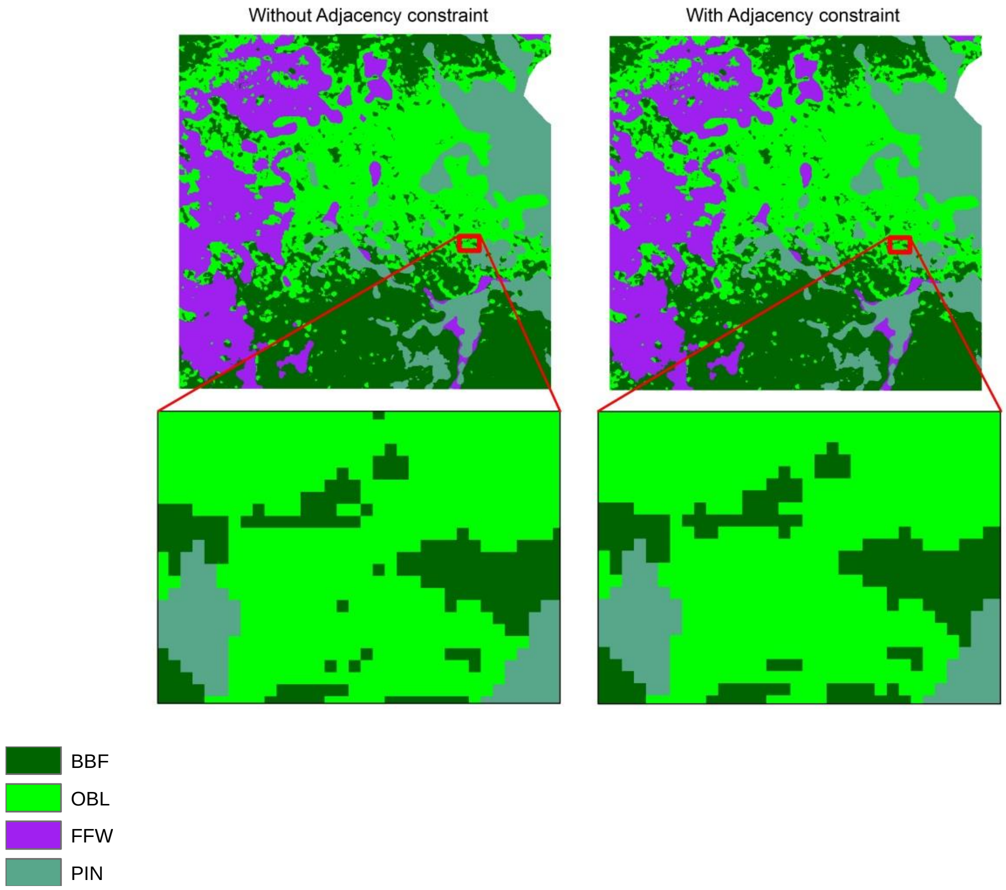


Figure 5.6. Composition of two results showing results for adjacency constraints. The left map belongs to a model without adjacency constraints. The right map belongs to a model with adjacency constraints.

Minimum and Maximum constraints

The use of minimum and maximum area constraints defines a specific number of hectares that must be assigned to each land use. These constraints are relevant to acquire a distributed landuses classes for the entire area and they also define feasible and infeasible solutions for a specific scenario. This FOM includes the capacity to user to specify certain number of minimum and maximum constraints for the four landuse classes. In Figure 5.7, three models were evaluated to test the validity of the FOM in terms of minimum and maximum constraints. If these constraints are omitted (Figure 5.7, upper left), results of the spatial optimization are expected to depend upon the land use class coefficients from the DMC (section 4.2). First of all, PIN landuse class, which is the most resilient land use class ($\beta_0 = -5.9867$), is assigned to its entire feasible area. Then, in comparing the feasible areas of the landuse class that are feasible of the entire study area (i.e., BBF and OBL), the OBL is more resilient ($\beta_0 = -7.0133$) that BBF ($\beta_0 = -9.1224$), therefore, the 16% of PIN and 78% of OBL were assigned to the study area as expected (the objective function value is 1.175461 10^9). If we constraint a minimum area for OBL of one hundred thousands of hectares, the results confirm that minimum area constraints are nonbinding. The areas percentage, pattern of location (Figure 5.7, upper right), and objective function value (1.175461 10^9) conserved the values of previous model (Figure 5.7, upper left). Alternatively, as soon as we constraint OBL to a maximum area of one hundred thousands of hectares, we expect not only the model locates other land use classes (Figure 5.7, lower center) but we also expected that the objective function value will increase (1.175461 10^9 to 1.20023 10^9).

Budget

Given that (a) some cost was involved in applying every land use, and (b) FOM required that each raster cell be assigned to some land use, we anticipate there would be some minimum budget level below which FOM would fail to find a solution. Further, we assumed that there would be some maximum budget level where each raster cell had been assigned to its most

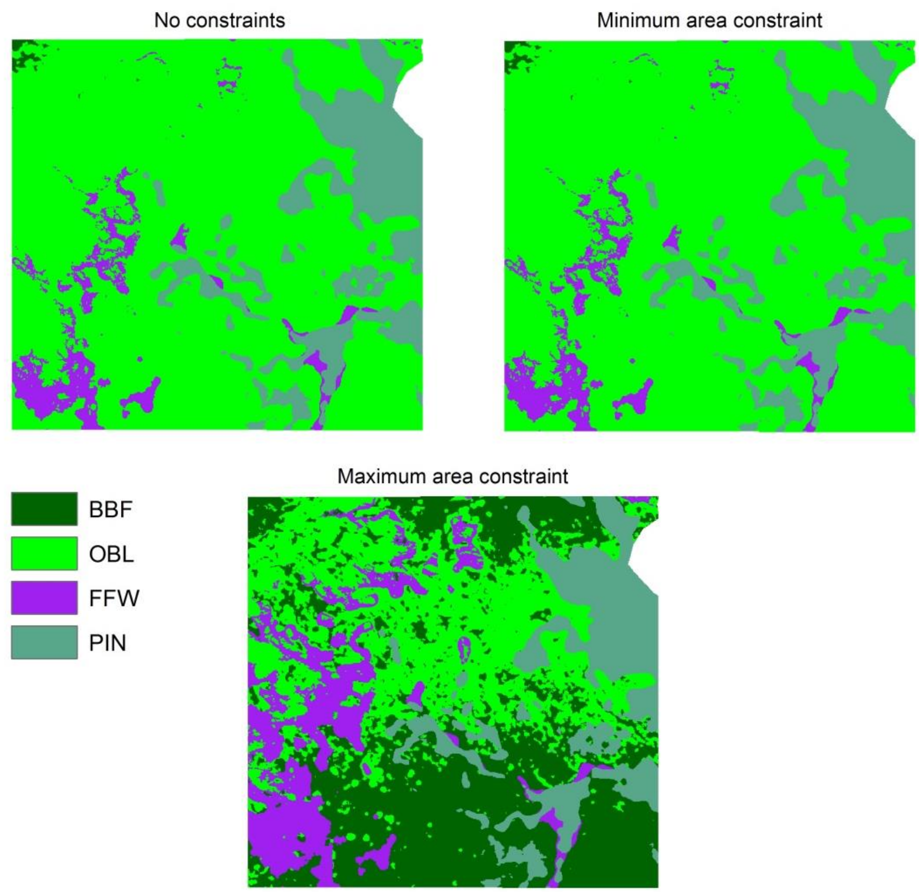


Figure 5.7. Three FOM models with no constraint (upper left), minimum area constraint (upper right), and maximum area constraint (bottom center).

beneficial use (subject to feasibility, area constraints, adjacency constraints, and so forth – all limiting factors other than the budget) and no additional benefit would be realized by increasing the budget. These expectations were tested using the analyses described in Table 5.1. The results in Table 5.1 imply that both the minimum and maximum budget levels just described do exist, and both fall between $ 8-9 millions.

Figure 5.8 shows that the budget changes described in Table 5.1 did not have major impact on the spatial pattern of land use allocations or on the percentage of the area assigned to each landuses classes. While land use changes did occur on the individual cell level, overall patterns at the regional scale did not change appreciably.

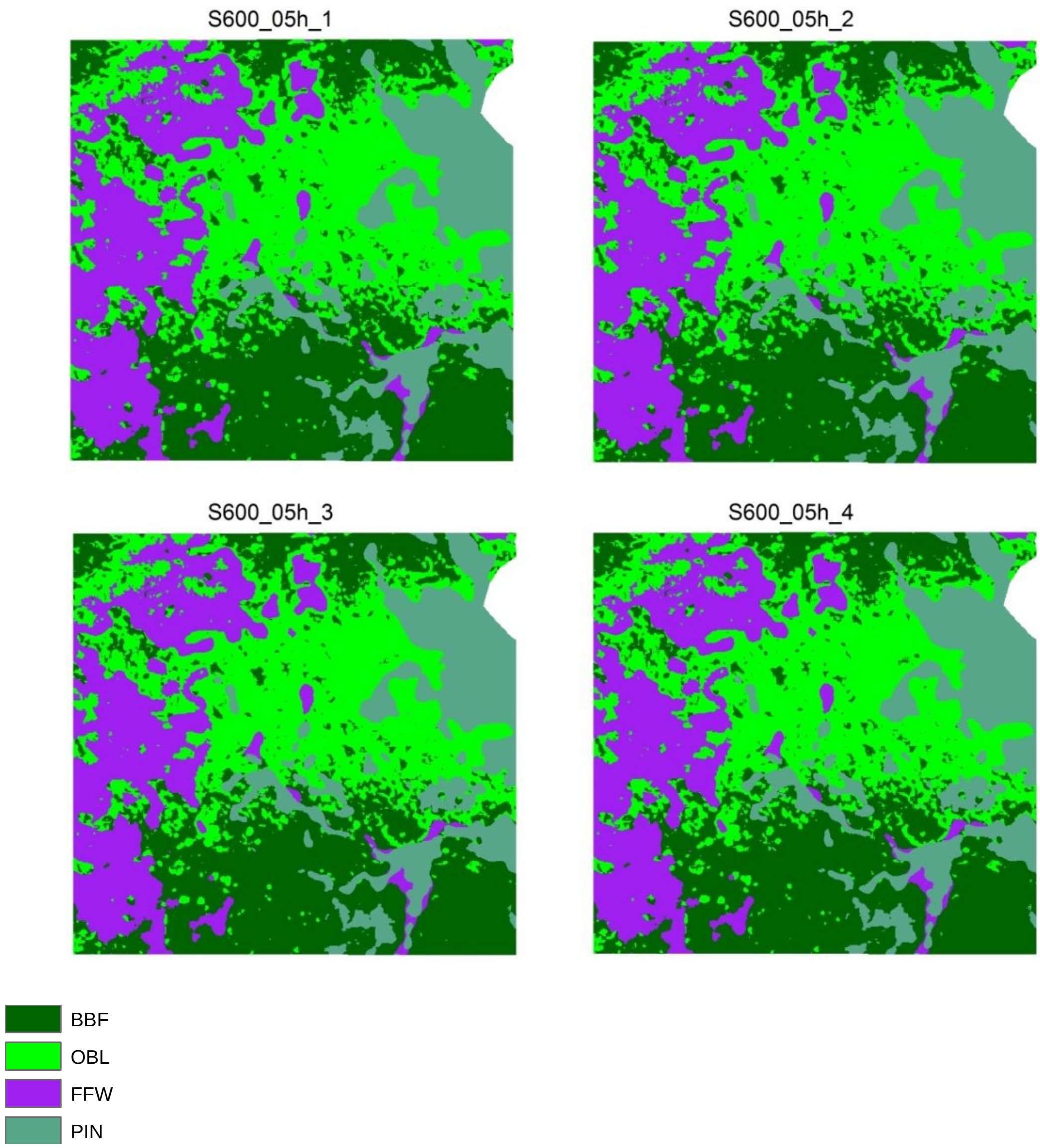


Figure 5.8. Illustration of similar pattern and area percentage for four models applying same minimum and maximum area constraints and same cost per hectares, the variation is in the budget constraint.

Table 5.1. Solutions of the FOM implementing invariable minimum and maximum area and cost per hectare for each land use class.

Id	Model Name	Min/Max Area	Cost / ha ($)	Percentage results (%)	Budget ($ million)	Objective function value (10^9)
1	S600_05h_1	Min BBF: 92 Min OBL: 92 Min FFW: 62 Min PIN: 35	BBF 20 OBL 25 FFW 30 PIN 40	BBF 30.93 OBL 32.11 FFW 20.84 PIN 16.13	10	1.206027
2	S600_05h_2	Min BBF: 92 Min OBL: 92 Min FFW: 62 Min PIN: 35	BBF 20 OBL 25 FFW 30 PIN 40	BBF 30.93 OBL 32.11 FFW 20.84 PIN 16.13	9	1.206027
3	S600_05h_3	Min BBF: 92 Min OBL: 92 Min FFW: 62 Min PIN: 35	BBF 20 OBL 25 FFW 30 PIN 40	BBF 30.93 OBL 32.11 FFW 20.84 PIN 16.13	8.5	1.206027
4	S600_05h_4	Min BBF: 92 Min OBL: 92 Min FFW: 62 Min PIN: 35	BBF 20 OBL 25 FFW 30 PIN 40	BBF 31.36 OBL 31.68 FFW 20.84 PIN 16.12	8	1.206346
5	S600_05h_5	Min BBF: 92 Min OBL: 92 Min FFW: 62 Min PIN: 35	BBF 20 OBL 25 FFW 30 PIN 40	--	7	Infeasible

As a second effort to provide evidence of budget validity in the FOM, four more models were evaluated employing extreme values in the cost of each land use class (Table 5.2 and Figure 5.9). By decreasing both the minimum area constraint and the cost of the BBF and OBL land uses, low budgets of 4 – 5 million can produce feasible solutions. This is due in no small part to the large feasible areas of BBF and OBL. Moreover, the spatial patterns of land use allocations and the percentages of the area allocated to each land use change dramatically amongst these models due to the extreme values used in the cost per hectare for each landuse.

Table 5.2. Four scenarios are presented to test the validity of the FOM. The variation of the cost per land use is presented in the four models.

Id	Model Name	Min/Max Area	Cost / ha ($)	Percentage results (%)	Budget ($ million)	Objective function value (10^9)
1	S600_05h_6	Min BBF: 30 Min OBL: 30 Min FFW: 20 Min PIN: 10	BBF 1 OBL 5 FFW 100 PIN 120	BBF 10.1 OBL 78.12 FFW 6.72 PIN 5.06	5	1.249815
2	S600_05h_7	No minimum /maximum	BBF 1 OBL 5 FFW 100 PIN 120	BBF 0.50 OBL 89.21 FFW 0 PIN 10.28	5	1.21313
3	S600_05h_8	No minimum /maximum	BBF 20 OBL 25 FFW 30 PIN 40	BBF 78.89 OBL 7.27 FFW 0.00 PIN 15.84	7	1.239120
4	S600_05h_9	No minimum /maximum	BBF 1 OBL 5 FFW 100 PIN 120	BBF 0.29 OBL 77.7 FFW 5.88 PIN 16.12	10	1.17546

<u>Physical area (Elevation and Slope)</u>

As another check of the plausibility of FOM results, we evaluated the model's outputs with regard to terrain factors. For instance, model S600_05h_1 (Figure 5.10, upper left), which is a model with minimum area for four landuse classes and high budget, prefers to allocate the OBL land use to areas of high elevation (Figure 5.10, lower left). The model S600_05h_9 (Figure 5.10, upper right), which is a model with no minimum area constraint for BBF, allocates the BBF in not only high elevation but also low slope (Figure 5.10, lower right). This result can be explained because elevation and slope were significant explanatory variables for BBF and OBL to measure the potential damage in the logistic regression. As mentioned previously, the spatial pattern of distribution of BBF and OBL are associated with DMC. In order to obtain more realistic landuses pattern (similar spatial distribution for FFW and PIN), at least the elevation (and/or slope) has to be included as explanatory variable in the logistic model.

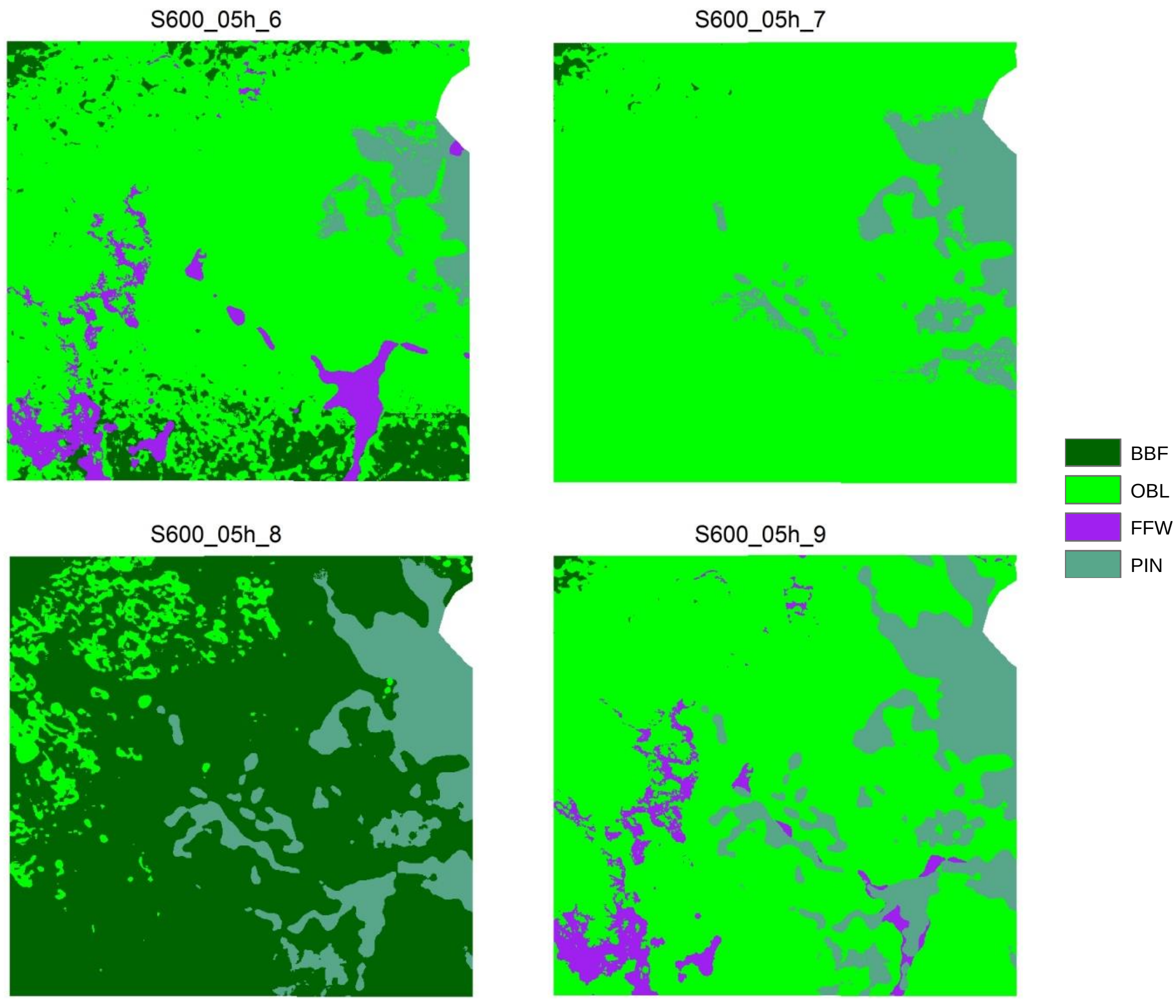


Figure 5.9. FOM models implementing extreme values by decreasing the minimum area constraint and interchanging considerable the cost per hectares of land use classes.

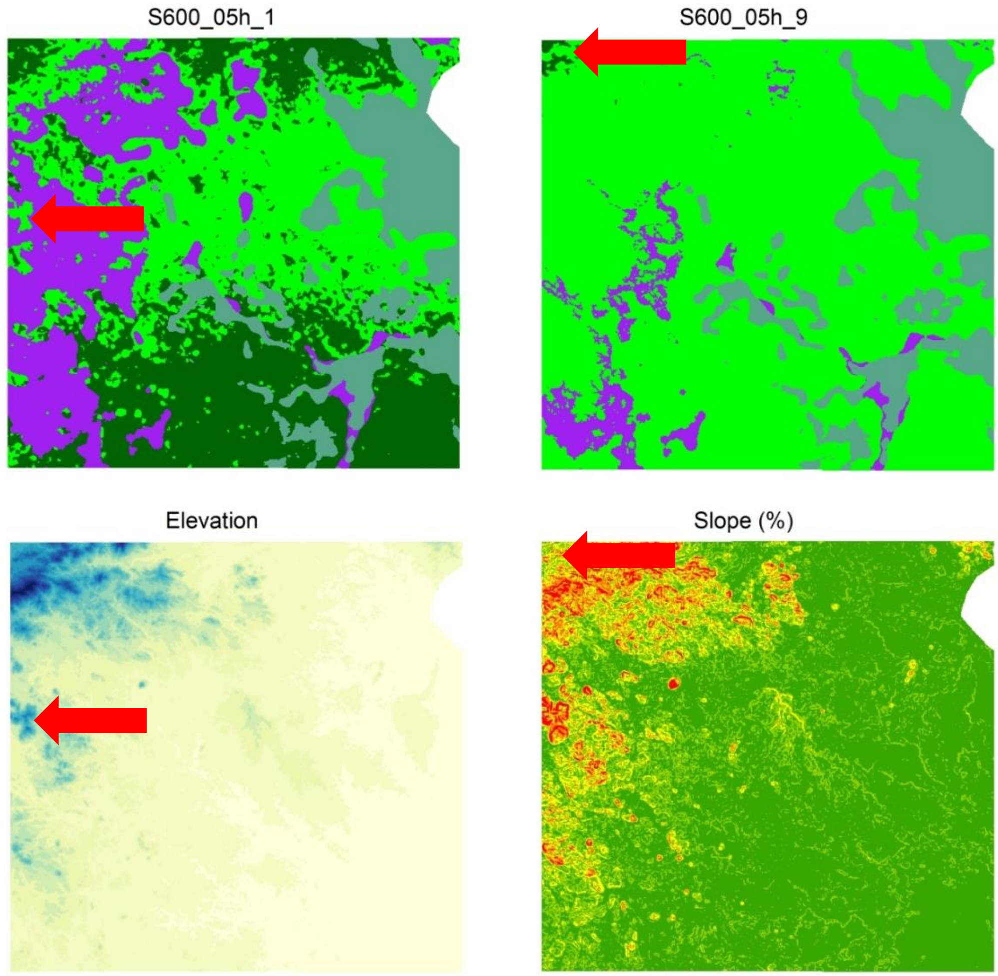


Figure 5.10. A map portraying the influence of elevation and slope for BBF and OBL. The upper left map was implemented using the model S600_05h_1 from Table 5.1. The upper right is the model S600_05h_9 from Table 5.2. The lower left portrays the Digital Elevation Model (m). The lower right map portrays the slope in percentage.

Storm frequency and intensity

It is expected that if a model were to be implemented using a single hurricane, its output would reflect the spatial patterns seen in that hurricane's predicted potential damage map. Furthermore, as the number of hurricanes used in the model increases, we expected that the model's outputs would exhibit an increasingly diversified spatial structure. This phenomenon can be seen in Figure 5.11. When the model was implemented with five hurricanes (Figure 5.11, upper left), a relatively simple pattern of land uses OBL in the central region and bands of the other three land uses to the north, south, east and west of this central region is observed. With fourteen hurricanes (Figure 5.11, upper right), this pattern is much less pronounced; the BBF landuse has encroached on many of the areas formally assigned to OBL (Figure 5.11, lower center).

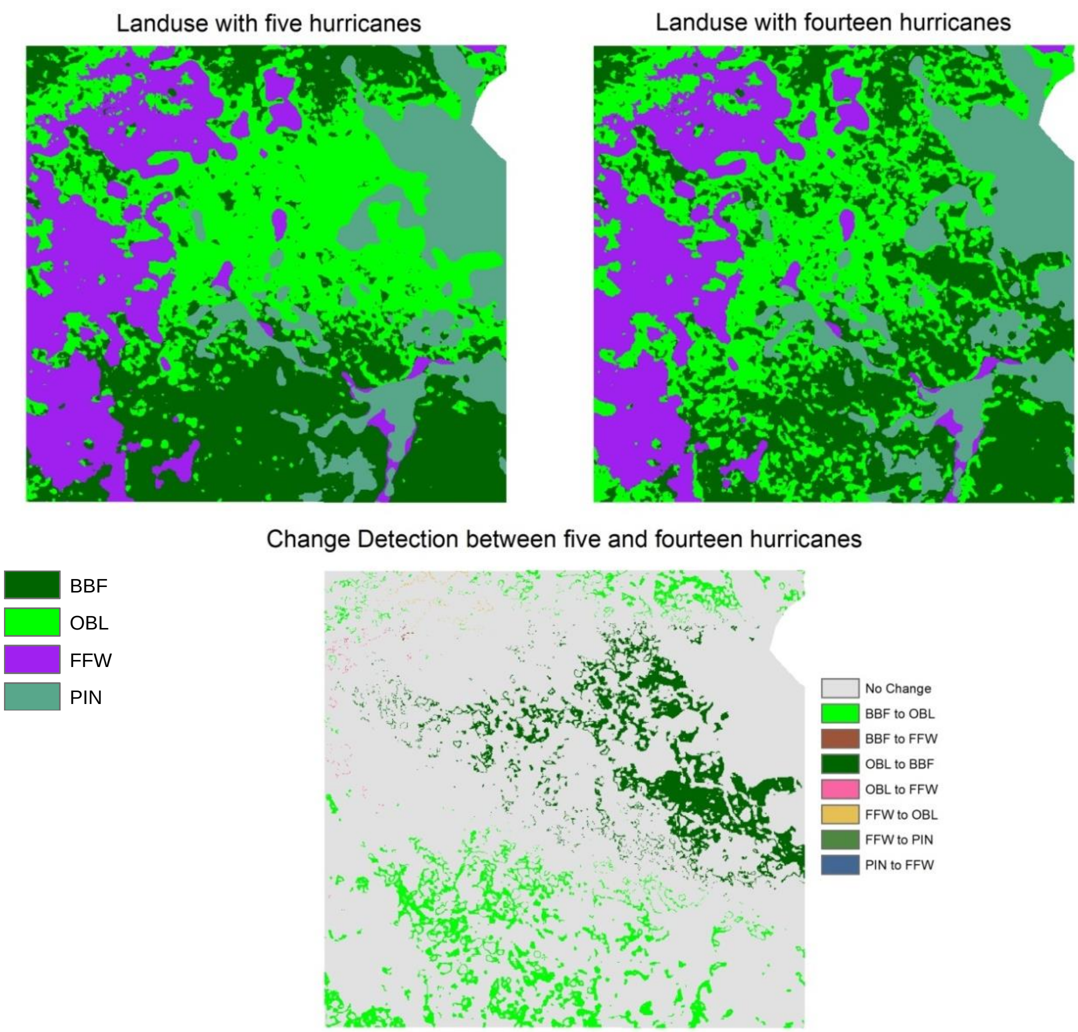


Figure 5.11. Map showing the change detection implementing the FOM using five and fourteen hurricanes.

5.2.2.2 Sensitivity Analysis

A sensitivity analysis was conducted to test the robustness of the FOM. The questions that were considered in the sensitivity analysis were: (1) how increasing / decreasing minimum area constraints impacted feasible solutions, (2) how budgets impact the resilience of the landscape against hurricane damages, and (3) how the model responded to minor perturbations in the cost of implementing each land use.

In order to evaluate the interrelated impacts of the available budget, land use implementation costs, and area constraints, a simple three-way experiment was conducted. The experimental variables were budget (two amounts were investigated, 9 million and 10 million), land use implementation costs (three levels were evaluated: the base costs that represent the author's best estimate of actual costs, and two artificial cost levels where the base costs were changing costs proportionally), and area constraints (two levels were testing, higher minimum areas that represents between 10-30% of total area and lower minimum areas constraints that represent between 3-10% of total areas for the landuses classes) (Table 5.3). The response variables were (1) whether or not the FOM was able to find a feasible solution, and if so (2) the value of the model's objective function.

The sensitivity analysis revealed that the experimental variable with the most impact was the relative values of landuse implementation costs ($/ha).The sensitivity analysis (Table 5.3) suggests that forcing the FOM to use altered landuse implementation costs largely determines the feasibility of FOM solutions. For instance, despite changing the available budget and the minimum area constraints, feasible solutions were found for all of the S600_05h_SA1 family of models, all of which include the base implementation cost. In this model, as expected, the objective function recorded better solutions (lower values) with lower (less restrictive) minimum area constraints. The interpretation is that with higher minimum area constraints, the model needs to select landuse classes with higher return values (for example, the BBF landuse) to find a feasible solution that satisfies the minimum area requirements for these less desirable landuses. These results also imply that the ceiling for the budget is around $9 million; increasing the budget from $9 million to $10 million did not produce any increase in the objective value, so optimal landuse allocations were possible at the lower budget level.

Table 5.3. Sensitivity analysis of implementation cost ($/ha) of each landuse class using two budgets and higher / lower minimum area constraints.

Constraints	S600_05h_SA1 Estimated cost		S600_05h_SA2		S600_05h_SA3	
Budget ($ million)	9	10	9	10	9	10
Cost per landuse	BBF 20 OBL 25 FFW 30 PIN 40	BBF 20 OBL 25 FFW 30 PIN 40	BBF 20 OBL 50 FFW 60 PIN 80	BBF 20 OBL 50 FFW 60 PIN 80	BBF 20 OBL 35 FFW 45 PIN 60	BBF 20 OBL 35 FFW 45 PIN 60
Min area (thousand/ ha)	BBF 92 OBL 92 FFW 62 PIN 35	BBF 92 OBL 92 FFW 62 PIN 35	BBF 92 OBL 92 FFW 62 PIN 35	BBF 92 OBL 92 FFW 62 PIN 35	BBF 92 OBL 92 FFW 62 PIN 35	BBF 92 OBL 92 FFW 62 PIN 35
Solution	Feasible Solution	Feasible Solution	Infeasible Solution	Infeasible Solution	Infeasible Solution	Infeasible Solution
Objective Value (10^9)	1.206027	1.206027	--	--	--	--
Min area (thousand/ ha)	BBF 30 OBL 30 FFW 20 PIN 10	BBF 30 OBL 30 FFW 20 PIN 10	BBF 30 OBL 30 FFW 20 PIN 10	BBF 30 OBL 30 FFW 20 PIN 10	BBF 30 OBL 30 FFW 20 PIN 10	BBF 30 OBL 30 FFW 20 PIN 10
Solution	Feasible Solution	Feasible Solution	Feasible Solution	Feasible Solution	Feasible Solution	Feasible Solution
Objective Value (10^9)	1.18022	1.18022	1.285537	1.24553	1.220881	1.200808

Conversely, if the base implementation cost is slightly increased (the costs for BBF are unchanged, and the remaining landuses are changing proportionally) in the second (OBL), third (FFW) and fourth (PIN) landuses; the FOM cannot produce a feasible solution under the higher area minimum constraints (i.e., models S600_05h_SA2 and S600_05h_SA3). Under these scenarios, there is not enough money in the budget to implement the higher cost landuses in sufficient areas to meet the higher minimum area constraint.

Under other scenarios, the impact of budget increases is clearly visible. For example, in both models S600_05h_SA2 and S600_05h_SA3, the objective function values of 1.24553 10^9 and 1.200808 10^9 with 10 million are more optimal than the 1.285537 and 1.220881 produced with 9 million budget. In these scenarios, higher budgets allow the model to utilize lower risk landuses even though they are more expensive than those selected under tighter budgets.

Similar scenarios were implemented with inverting the costs (Table 5.4). In these models, the estimated implementation costs were inverted between landuse classes (making the most expensive land use the least expensive and so forth). The least and most expensive implementation costs belong to PIN (most resilient landuse) and BBF (less resilient landuse), respectively. Comparing the estimated cost (S600_05h_SA1) with its inverted (S600_05h_SA4), the FOM found infeasible area with higher minimum area constraint and budget of 9 million. In this inverted scenario (S600_05h_SA4), the FOM includes a limited budget, and it is forced to allocate a considerable area of BBF, which has a higher implementation cost. In contrast, if more economic resources area available (higher minimum area and 10 million), the FOM can find a feasible solution. If the restriction of minimum area is decreased, feasible solutions can be found for both budget levels because the model is not forced to allocate BBF landuse with the higher implementation cost. Interesting results can be concluded considering the models S600_05h_SA1 and S600_05h_SA4. Given the implementation costs and the budget level and implementing the lower minimum area constraint of these models, the budget is not constraining because the objective function value is identical the same (1.18022 10^9).

Table 5.4. Sensitivity analysis of invert implementation cost ($/ha) of each landuse classes using two budgets and higher / lower minimum area constraints.

Constraints	S600_05h_SA4 Inverse S600_05h_SA1		S600_05h_SA5 Inverse S600_05h_SA2		S600_05h_SA6 Inverse S600_05h_SA3	
Budget ($ million)	9	10	9	10	9	10
Cost per landuse	BBF 40 OBL 30 FFW 25 PIN 20	BBF 40 OBL 30 FFW 25 PIN 20	BBF 80 OBL 60 FFW 50 PIN 20	BBF 80 OBL 60 FFW 50 PIN 20	BBF 60 OBL 45 FFW 35 PIN 20	BBF 60 OBL 45 FFW 35 PIN 20
Min area (thousand/ ha)	BBF 92 OBL 92 FFW 62 PIN 35	BBF 92 OBL 92 FFW 62 PIN 35	BBF 92 OBL 92 FFW 62 PIN 35	BBF 92 OBL 92 FFW 62 PIN 35	BBF 92 OBL 92 FFW 62 PIN 35	BBF 92 OBL 92 FFW 62 PIN 35
Solution	Infeasible Solution	Feasible Solution	Infeasible Solution	Infeasible Solution	Infeasible Solution	Infeasible Solution
Objective Value (10^9)	--	1.20603	--	--	--	--
Min area (thousand/ ha)	BBF 30 OBL 30 FFW 20 PIN 10	BBF 30 OBL 30 FFW 20 PIN 10	BBF 30 OBL 30 FFW 20 PIN 10	BBF 30 OBL 30 FFW 20 PIN 10	BBF 30 OBL 30 FFW 20 PIN 10	BBF 30 OBL 30 FFW 20 PIN 10
Solution	Feasible Solution	Feasible Solution	Infeasible Solution	Infeasible Solution	Infeasible Solution	Infeasible Solution
Objective Value (10^9)	1.18022	1.18022	--	--	--	--

In conclusion, these sensitivity analyses suggest that feasible solutions are strongly regulated by the interaction of four factors: (1) the feasible area assigned to each landuse, (2) the minimum and maximum area constraints for each landuse, (3) landuse implementation costs, and

(4) the available budget. Adjusting these factors largely determines the feasibility of the model’s results.

CHAPTER 6

SUMMARY AND CONCLUSION

A Forest Optimization Model has been developed in order to minimize the risks posed by hurricanes in Eastern Nicaragua, Central America. This optimization model employed data measured after Hurricane Felix (2007) and utilized model-generated synthetic hurricanes and integer-programing based optimization techniques. The model was implemented in a GIS-based environment and handled the most important constraints such as adjacency, minimum and maximum area, and budget. The conclusions and recommendations of this research suggest the following:

6.1 Conclusions of research

6.1.1 Forest Optimization Model

- The FOM is flexible. The use of feasible areas allows the model to take into account the environmental and geographic realities in the study region. Area constraints can be used to capture managerial realities. The budget constraint allows flexibility for the user to analyze and weigh the tradeoffs that are associated with different budget levels. If the budget constraint has to be considered, a previous analysis between cost per hectare of the land use classes and the minimum and maximum area constraints has to be performed.

- The inclusion of adjacency constraint in the FOM has the greatest impact on execution time of any of the components of the model. This factor is exponentially related to time required to solve the optimization model. However, it is necessary to include the adjacency factor into the system to produce realistic models. The previous statement implies that adjacency and number of hurricanes will become the limiting factors that determine the maximum size of problems that can be handled in this approach.

6.1.2 Nature of Eastern Nicaragua and data collection

- As in most environmental modeling, the results of this study are applied to a specific location. It is important to note: 1) the data employed to develop the model (e.g., historic hurricanes features, land use, and DEM) support generalization only to the east of Central America, and 2) due to the information available, this study is based upon a case study of the damages caused by a single recent hurricane. Furthermore, because this study investigates only natural resource impacts, specifically forest management, the quantification of hurricane impacts on social problems (e.g., village destruction and death) is beyond the scope of this study.
- This research suggests that land managers (e.g., Inafor, Marena, Ineter, and local and regional government) can achieve realistic land management plans which minimize the risks posed by hurricanes. Since an increase in frequency and intensities of hurricanes is expected in eastern Nicaragua, this ability can serve as the main guide for future natural resource management actions.

- The data employed in the data model calibration (DMC) (Inafor 2007) contained many errors due to misleading classification of the level of damage of Hurricane Felix (2007). There was confusion regarding the damage ratings in category 3. Accordingly, this category exhibited the greater residuals seen in the DPM. An improved data collection methodology should be implemented in future damage rating collection studies.

6.2 Recommendations of future research

6.2.1 Forest Optimization Model

- In future research, the FOM can be extended to incorporate the temporal problem. The forest activities could be redefined as time sensitive across predefined planning periods. Thus, instead of having a "harvest timber" activity, the FOM could include activities such as "harvest timber - period 1," "harvest timber - period 2," and so forth. Management units could then be assigned to each forest activity at any planning period, subject to constraints designed to prevent temporally impossible or incompatible activities (e.g., a single management unit could not be harvested in consecutive time periods because it would not have sufficient time to regenerate between periods). Furthermore, temporal constraints could be added to the model to capture conditions in any specific planning period.
- Access issues can be addressed in the model in order to ensure that the model's results can be implemented by land managers. Access constraints can be handled using both existing road networks and potential access networks (i.e., roads that do not currently exist but can be built if needed to access various management units).

- Adjacency constraints can be improved with a more sophisticated method that includes more than four neighbors and specific adjacency constraint per land use.

6.2.2 Nature of Eastern Nicaragua and data collection

- To avoid the data quality issues this study encountered in building the DMC, future data collections efforts should strive to 1) capture an equivalent number of observations per land use (individual land uses and not aggregated land use classes), 2) extend the sampling flight path from the hurricane path to at least distance of 120 km (greater than the scale factor of potential damage model), and 3) capture an increased number of observations in the Atlantic coast region.

REFERENCES

ACAN-EFE. 2007. "Nicaragua Es Alto Emisor De CO2." *LA PRENSA*.

Adams, D. M., R. J. Alig, J. M. Callaway, B. A. McCarl, and S. M. Winnett. 1996. *The Forest and Agricultural Sector Optimization Model (FASOM): Model Structure and Policy Applications*. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station. http://www.fs.fed.us/pnw/pubs/pnw_rp495.pdf.

Aguirre, Lesly M. and Carlos Salinas-Maldonado. 2007. "Huracanes Azote De Nicaragua." *LA PRENSA*.

Beven, Jack. 2008. *Tropical Cyclone Report: Hurricane Felix* : National Hurricane Center.

Browner, C. M. "Watershed Approach Framework: What is a Watershed Approach?." United States Environmental Protection Agency, accessed April 17, 2011, http://water.epa.gov/type/watersheds/framework.cfm.

Center of Climate and Energy Solutions. "Hurricanes and Climate Change." Center of Climate and Energy Solutions, accessed August/2014, 2014, http://www.c2es.org/science-impacts/extreme-weather/hurricanes.

Emanuel, Kerry. 2013. *Article - A Statistical Deterministic Approach*.

Emanuel, Kerry. 2005. *Increasing Destructiveness of Tropical Cyclones Over the Past 30 Years*. Vol. 436. doi:10.1038/nature03906. http://dx.doi.org/10.1038/nature03906.

Emanuel, Kerry, Sai Ravela, Emmanuel Vivant, and Camille Risi. 2006. "A Statistical Deterministic Approach to Hurricane Risk Assessment." *Bulletin of the American Meteorological Society* 87 (3): 299-314. doi:10.1175/BAMS-87-3-299. http://dx.doi.org/10.1175/BAMS-87-3-299.

ESRI. "About the ESRI Grid Format." ESRI, accessed August/27, 2014, http://webhelp.esri.com/arcgisdesktop/9.2/index.cfm?TopicName=About_the_ESRI_grid_format.

Frelich, Lee E. 2002. *Forest Dynamics and Disturbance Regimes Studies from Temperate Evergreen-Deciduous Forests*. New York: New York : Cambridge University Press, 2002.

Gent, P. R., G. Danabasoglu, L. J. Donner, M. M. Holland, E. C. Hunke, S. R. Jayne, D. M. Lawrence, et al. 2011. "The Community Climate System Model Version 4." *Journal of Climate* 24: 4973-4991.

Gibson, I. A. S. and T. Jones. 1977. "Monoculture as the Origin of Major Forest Pests and Diseases." *Symposium of the British Ecological Society* 1976 (Pub. 1977) (18th): p. 139-161.

GIZ-GFA Consulting Group- MASRENACE. 2010. *Análisis Multitemporal Del Cambio De Uso Del Suelo En Base a Imágenes Satelitales De Los Territorios Indígenas De Mayangna Sauni as , Mayangna Sauni Bas , Sikilta, MatungBak/Sauni Arungka, SIPBAA, Layasiksa Y El Área Afectada Por El Huracán Félix En 2007 Para El Período De Tiempo 2005 – 2007/08 En Los Departamentos De Jinotega Y La RAAN, Nicaragua*. Managua, http://www.refworks.com/refworks2/default.aspx?r=references|MainLayout::init#Nicaragua : German Agency for International Cooperation.

———. . 2008. *Análisis Multitemporal Aplicando Imágenes Satélite Para La Cuantificacion De Los Cambios De Uso De La Tierra Y Cobertura En Bosawas-RAAN Y En Los Departamentos De Rivas, Carazo Y Granada.* Managua: MASRENACE.

Goycoolea, Marcos, Alan T. Murray, Francisco Barahona, Rafael Epstein, and Andrés Weintraub. 2005. "Harvest Scheduling Subject to Maximum Area Restrictions: Exploring Exact Approaches." *Operations Research* 53 (3): 490-500. http://www.jstor.org/stable/25146883.

Grimm, Volker, Eric Schmidt, and Christian Wissel. 1992. "On the Application of Stability Concepts in Ecology." *Ecological Modelling* 63 (1–4): 143-161. doi:http://dx.doi.org/10.1016/0304-3800(92)90067-O.

Harmeling, Sven and David Eckstein. 2012. *Global Climate Risk Index 2013*. Berlin: Germanwatch e.V. http://germanwatch.org/fr/download/7170.pdf.

Inafor. 2007. Evaluación de daños al ecosistema forestal ocasionados por el huracán félix. Managua, Nicaragua: National Forestry Institute of Nicaragua, (accessed May, 2009).

Irish, J. L., D. T. Resio, and J. J. Ratcliff. 2008. "The Influence of Storm Size on Hurricane Surge." *Journal of Physical Oceanography* 38: 2003-2013. doi:10.1175/2008JPO3727.1.

Keles, S. 2010. "Forest Optimisation Models Including Timber Production and Carbon Sequestration Values of Forest Ecosystems: A Case Study." *International Journal of Sustainable Development & World Ecology* 17 (6): 468-474. doi:10.1080/13504509.2010.519574. http://search.ebscohost.com/login.aspx?direct=true&db=a9h&AN=55473848&site=ehost-live.

Knutson, T. R., J. J. Sirutis, S. T. Garner, I. M. Held, and R. E. Tuleya. 2007. "Simulation of the Recent Multidecadal Increase of Atlantic Hurricane Activity using an 18-km-Grid Regional Model." *American Meteorological Society* 88 (10): 1549 - 1565. doi:10.1175/BAMS-88-10-1549. http://dx.doi.org/10.1175/BAMS-88-10-1549.

Kovacs, J. M., M. Blanco-Correa, and F. Flores-Verdugo. 2001. "A Logistic Regression Model of Hurricane Impacts in a Mangrove Forest of the Mexican Pacific." *Journal of Coastal Research* 17 (1): 30-37. http://www.jstor.org/stable/4300147.

Li, Chao, Jianwei Liu, Raffaele Lafortezza, and Jiquan Chen. 2011. "Managing Forest Landscapes Under Global Change Scenarios." In *Landscape Ecology in Forest Management and Conservation Challenges and Solutions for Global Change*. Beijing : Heidelberg ; New York: Beijing : Higher Education Press; Heidelberg ; New York : Springer.

Lin, Yu-Pin, Yun-Bin Lin, Yen-Tan Wang, and Nien-Ming Hong. 2008. "Monitoring and Predicting Land-use Changes and the Hydrology of the Urbanized Paochiao Watershed in Taiwan using Remote Sensing Data, Urban Growth Models and a Hydrological Model." *Sensors* 8 (2): 658-680.

McNulty, Steven G. 2002. "Hurricane Impacts on US Forest Carbon Sequestration." *Environmental Pollution* 116, Supplement 1 (0): S17-S24. doi:10.1016/S0269-7491(01)00242-1.

Meinshausen, Malte, S. J. Smith, K. Calvin, J. S. Daniel, M. L. T. Kainuma, J-F Lamarque, K. Matsumoto, et al. 2011. "The RCP Greenhouse Gas Concentrations and their Extensions from 1765 to 2300." *Climate Change* (109): 213-241.

Mendoza, G. and J. Vanclay. 2008. "Trends in Forestry Modelling." *CAB Reviews: Perspectives in Agriculture, Veterinary Science, Nutrition and Natural Resources* 3 (10). doi:http://dx.doi.org/10.1079/PAVSNNR20083010.

Ministerio del Ambiente y los Recursos Naturales. 2008. Nicaragua... unida frente al cambio climatico! Managua, Nicaragua.

Morel, B. 2007. "“Félix” Dejó Cerca De 300 Niños Huérfanos." *LA PRENSA*, September 19, 2007. http://archivo.laprensa.com.ni/archivo/2007/septiembre/19/noticias/ultimahora/216493.shtml.

Murray, A. T. and A. Weintraub. 2002. "Scale and Unit Specification Influences in Harvest Scheduling with Maximum Area Restrictions." *Forest Science* 48 (4): 779-789.

National Center for Atmospheric Research. "Hurricanes, Typhoons, Cyclons: Background on the Science, People, and Issues Involved in Hurricane Research." University Corporation for

Atmospheric Research, accessed August/21, 2014, https://www2.ucar.edu/news/backgrounders/hurricanes-typhoons-cyclones.

National Weather Service. "Tropical Cyclone Climatology." NOAA, accessed March/9, 2014, http://www.nhc.noaa.gov/climo/.

O'sullivan, David and David Unwin. 2010. *Geographic Information Analysis*. Second Edition ed. New Jweswy: John Wiley & Sons.

Schneider, et al. 2008. "The European Forest and Agricultural Sector Optimization Model – EUFASOM." Gothenburg, Sweden, .

Stanturf, J., S. Goodrick, and K. Outcalt. 2007. "Disturbance and Coastal Forests: A Strategic Approach to Forest Management in Hurricane Impact Zones." *Forest Ecology and Management* 250: 119 - 135. doi:10.1016/j.foreco.2007.03.015.

Stevens, W. D. "Flora De Nicaragua." Missouri Botanical Garden, accessed July/22, 2013, http://www.mobot.org/MOBOT/research/nicaragua/vegetacion.shtml.

Tahal Consulting Engineers and Tecnoplan. 1978. *Potencial De Desarrollo Agropecuario Y Rehabilitación De Tierras En La Costa Atlántica-Nicaragua*. Managua, Nicaragua.

Tong, Daoqin and Alan T. Murray. 2012. "Spatial Optimization in Geography." *Annals of the Association of American Geographers* 102 (6): 1290-1309. doi:10.1080/00045608.2012.685044. http://dx.doi.org.libproxy.utdallas.edu/10.1080/00045608.2012.685044.

Uriarte, M. and M. Papaik. 2007. "Hurricane Impacts on Dynamics, Structure and Carbon Sequestration Potential of Forest Ecosystems in Southern New England, USA." *Tellus: Series A* 59 (4): 519-528. doi:10.1111/j.1600-0870.2007.00243.x. http://search.ebscohost.com/login.aspx?direct=true&db=a9h&AN=25779882&site=ehost-live.

Webster, P. J., G. J. Holland, J. A. Curry, and H. -R Chang. 2005. "Changes in Tropical Cyclone Number, Duration, and Intensity in a Warming Environment." *Science* 309: 1844-1846. doi:10.1126/science.1116448.

Young, K. R., M. A. Blumler, L. D. Daniels, T. T. Veblen, and S. S. and Ziegler. 2004. "Biogeography." In *Geography in America at the Dawn of the 21st Century*, edited by In C. Willmott and G. Gaile. eds. ed., 17-77. Oxford, UK: Oxford University Press.

Zimmerman, Jess K., Edwin M. Everham, Robert B. Waide, D. Jean Lodge, and Charlotte M. Taylor. 1994. "Responses of Tree Species to Hurricane Winds in Subtropical Wet Forest in

Puerto Rico: Implications for Tropical Tree Life Histories." *Journal of Ecology* 82 (4): 911-922. doi:10.2307/2261454.

VITA

Fernando Jose Mendoza Jara was born in the small town of Niquinohomo, Masaya, Nicaragua. After graduating as a Forestry Engineer from the National Agrarian University (UNA) in 2000, he began working as a professor at the "Faculty of Natural Resources and the Environment" at UNA in Nicaragua. Three of his proudest academic achievements include: (1) the Inter-American Development Bank Scholarship granted in 2002 to study a specialization in GIS at Agustin Codazzi Institute in Colombia, (2) the Fulbright Scholarship granted in 2006 to study the Geospatial Information Science master program (MS-GIS) at University of Texas at Dallas (UTD), and (3) the Organization of American States Scholarship granted in 2010 to study the PhD-GIS at UTD. During the PhD-GIS program, Fernando also worked as Teaching Assistant (TA) at UTD. He is a proud member of Phi Kappa Phi Honor Society - Chapter 316 at UTD, Golden Key International Honour Society, Fulbright Association North Texas Chapter, and the National Scholars Honor Society. His prime aim is to develop sophisticated tools in GIS and Remote Sensing to be employed in his home country, Nicaragua. Moreover, through teaching and implementing a series of GIS and Remote Sensing workshops, Fernando has been able to contribute to his community. His research areas are natural disaster, watershed management, mapping and classification of forest, study of biodiversity, soil resources mapping, and spatial optimization.