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Modeling Susceptibility of Forests to Hurricane Damage Based on Forest Ownership, Age, and Type

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By

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This study examined the severity of wind damage created by Hurricane Katrina in southeast Mississippi to determine how the disturbance was influenced by fragmentation based on different forest ownership groups (Non-corporate private forest, corporate private forest and public forest). MODIS-NDVI percent change products were coupled with ownership, rainfall, and Landsat based thematic maps depicting forest age and forest types using GIS techniques to examine potential contributing factors to possible damage for the study area. Multiple linear and binary logistic regression methods were used to explain the relationship between severity of damage and forest age, forest type, ownership, and rainfall. Results indicate that the NDVI percent change had a negative relationship with forest age diversity and a positive relationship with forest type diversity and rainfall. There was no clear and direct consistent relationship between NDVI percent change and forest ownership.

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CHAPTER I

INTRODUCTION

Forests are an important natural resource because of their role in influencing climate factors, regulating atmospheric composition, providing for carbon sequestration, supporting social and economic activities of many rural and urban communities around the world, and preserving biodiversity (McNulty, 2002; Butler and Leatherberry 2004). In Mississippi, forests account for 65 percent of the total land area (Smith et al. 2009). Developing future understanding of the geo-biophysical and ecological processes of these forests is important. There are different types of forestland ownership which vary in tract sizes, management practices, and uses. Smaller forest tracts tend to be associated with non-timber related activities while larger forest parcels are used for timber production (MIFI 2006). Increasing population density results in greater fragmentation of forests, which in turn, culminates in non-timber related activities and environmental services (Zhang et al. 2009). In the Eastern U.S., 75 percent of forestland is under private ownership (Smith et al. 2009). The three major forestland owner groups are: Corporate Private Forest (CPF), Non-Corporate Private Forest (NCPF) and publicly owned forestland. Corporate owners include forest industry, forest management companies, and timber investment managements organizations. NCPF consist of individuals, couples, estates, trusts, nongovernment organizations, clubs, associations and other unincorporated groups. Public forest consist of Federal, State, County and municipal governments (Smith et al. 2009). The predominance of family ownership of forestland in Mississippi has led to the division of large ownerships into smaller tracts through subdivision practices (MIFI 2006). In Mississippi, NCPF forest landowners typically own an average tract of 4 hectares (MIFI 2006).

Forestland fragmentation is a physical change associated with creating small tracts and can have deep effects on forest functionality (Twedt, et. al 1999). Benitez-Malvido (1998) found in the Amazonian Biological Dynamics Project, the density of tree seedlings declined dramatically from continuous forest to forest fragments. Similarly, the number of tree species was significantly higher in contiguous habitat areas than in fragmented patches of the same aggregate size. Alteration in stand size, ownership type, and management has many effects on wildlife habitat, management costs, and how forests are impacted by natural disasters.

The severity of wind damage may differ between the various forest owners because of different tract and stand size and management practices. In many forest types, initial clearcut harvesting of mature stands, is commonly followed up by windfall (Alexander 1964) and with no suitable forest management plan, the losses along the boundaries of adjacent forests can be huge (Alexander 1964). Fragmented forest zones tend to be highly vulnerable to wind damage because boundaries are more exposed to wind loading (Peltola et al. 1999). Therefore, wind can break into the core of forest canopy through increasing boundary density caused by parcelization and fragmentation. This has become a critical issue for forest owners, managers, policy makers and communities. A number of strategies have been suggested to solve this problem including the detection, analysis, modeling and prediction of hurricane disturbance (shear/blow down). In this regard, geographic information system (GIS) techniques with remote sensing data products were utilized in this study to examine how different stand size, ownership type, and management practices may be related to forest damage from Hurricane Katrina.

Hurricane Katrina made landfall on the 29th of August 2005 and it devastated the Louisiana and Mississippi Gulf Coasts (Oswalt and Oswalt 2008). A study by Wang and Xu (2009) indicated that Katrina created damage on an estimated 60% of the total forested land in the region. A number of local and regional characteristics such as climate, soil, and topographic factors have different impacts on forests exposure and vulnerability to hurricane disturbance (Mitchell 1995; Everham and Brokaw 1996; Tang et al. 1997; Lekes and Dandul 2000). Therefore, the distribution and intensity of the hurricane disturbance varies across the landscape. Over time, ownership changes, different management practices, and human activities of clearing of forested land for fields, roads, and power lines create a series of small, isolated pieces of forest; a process that led to high forest fragmentation.

According to Graumann et al. (2005), the Mississippi Institute for Forest Inventory (MIFI) and United States Forest Service Forest Inventory and Analysis (USFS FIA), Hurricane Katrina was responsible for over one and half million hectares of forest land damage and approximately 39 million m^3 of timber damage in SE forest land in Mississippi, an estimated monetary loss of $125 billion for the entire storm event.

Coastal regions are an important source of livelihood for about half of the world's population (Stanturf et al. 2007; Rodgers III et al. 2009). In the Southern United States, coastal areas are characterized by frequent hurricane incidence. Hurricane damage arises in the coastal zone and spreads through vast inland regions where remotely sensed data offer exclusive valuable information (Stanturf et al. 2007). There is an increasing need for hurricane damage mapping due to huge amount of environmental, social, and economical loss in forest resources. The use of remote sensing and GIS has become one of the most cost effective approaches and works extremely well for modeling, analyzing, and reporting information on natural resources and their changes. Change detection and monitoring involve the evaluation of temporal differences in land cover due to environmental conditions and human activities between multi-date images (Mas 1999).

The reception of images from environmental satellites began in the early 1970's with the launch of Landsat 1 and these images have been utilized for more than four decades to detect land cover changes. Change detection is one of the most common uses for repetitive satellite imagery and involves the comparison of two or more images of the same location taken at different points in time (Cohen et al. 1996). There are different approaches used to conduct change detection. These techniques have been applied for some time in many areas of natural resource and environment studies. Reasons to monitor change are to investigate the causes of change, to predict its significance, and to model or generate a scenario of change in the future. A large number of the studies in change detection have occurred in forestry where efforts have focused on finding methods to accurately estimate the amount of forest cover change over large areas. These methods could be very useful in assessment and estimating forest damage caused by natural disasters such as drought, ice damage, and wind damage.

Forest damage detection analysis must consider not only the biophysical properties of forests, but also the social and economic context in which the forests exist.

The fate of forests primarily lies in the hands of the people who own and manage forests. Landowners ultimately make the decisions that lead to parcelization, fragmentation, thinning, and harvesting. Understanding and predicting the implications of hurricane damage related to the socio-economic trends associated with parcelization and related management practices are important for the successful management of coastal forest ecosystems. By combining GIS and remote sensing data with land ownership, forest age, forest type, rainfall, spatial patterns of changes and potential effects of changes on susceptibility of forestland to hurricane damage were investigated in this study. Such information may provide useful knowledge to understand damage processes in order to model susceptibility of forests to damage in future hurricane events.

1.1 Literature Review

1.1.1 Forest Damage

Hurricanes obviously represent a severe climatic incident. Wind damage can happen nearly instantaneously in a disastrous storm or more slowly through time as new forest edges are exposed due to stem breakage or blow down (Savill 1983; Miller et al. 1987). Timber species in areas with frequent strong winds may be less vulnerable to catastrophic damage because they are adapted to greater environmental extremes. Also wind damage may be more severe when storm winds come from a direction other than prevailing winds (Ruel 1995; Kenworthy 1998; Zeng et al. 2004).

1.1.1.1 Site Dependencies

Trees on sites with soil conditions that limit root growth and depth are more susceptible to uprooting. Differences in wind damage along topographical slopes are more complicated and are often confused with tree species (crown and root morphology) and soil characteristics. Trees are morphologically different in their crown architecture and leaf shapes, distributions, and density, and therefore, they might exhibit different damage characteristics. For instance, tree species such as swamp tupelo *(Nyssa sylvatica var biflora* (Walter) Sarg*),* bald cypress *(Taxodium distichum* (L.) Rich*),* longleaf pine *(Pinus palustris* Miller*),* and live oak *(Quercus virginiana* Miller*)* have been shown to be highly resistant to hurricane wind damage (Gresham et al. 1991). The main morphological characteristics which enhance the resistance to wind damage in swamp tupelo and cypress was linked to buttressed boles and the defoliated habit and extensive lateral root system of cypress. In addition, longleaf pine is characterized by a large taproot and wide lateral root systems which increase anchorage. On the other hand, pond pines *(Pinus serotina* L.*),* water oaks *(Quercus negra* L.*),* and laurel *oaks (Quercus laurifolia* Bartram ex Willdenow*)* are sensitive to wind throw due to their shallow root systems in soils characterized by high water tables (Gresham et al. 1991). In addition to the aforementioned factors, the spatial pattern and severity of damage to forests is influenced by other factors that include intensity of the wind, topography, soil characteristics, height-to-diameter ratios, crown area, total height, canopy structure, spacing, recent thinning, and impacts of previous disturbance on generating exposed boundaries that make surrounding trees more vulnerable to wind damage (Zeng et al. 2004; Oswalt and Oswalt 2008). Species composition may also affect the degree of damage from hurricanes and represents a stand attribute that can be manipulated by forest managers. All these attributes are affected by the interest of the landowners and their management.

1.1.1.2 Remote Sensing Studies

Oswalt and Oswalt (2008) addressed four objectives in the study "Relationships Between Common Forest Metrics and Realized Impacts of Hurricane Katrina on Forest Resources in Mississippi." The first one was to see if inventory data gave evidence on damage zone assessment made using remotely sensed and climate data after Hurricane Katrina. The second objective was to see which one of the two tree groups (softwood or hardwood) was more susceptible to hurricane damage and does that susceptibility change with distance from landfall. The third objective considered measured stand characteristics and damage observations to determine the most important factors that influence vulnerability to damage on the stand level. Lastly, they wanted to see if the damage type (bole, branch, lean or wind throw) differs between tree species.

Oswalt and Oswalt (2008) used the same model that was utilized by the U.S. Forest Service (USFS), Southern Research Station (SRS), Forest Inventory and Analysis (FIA) program for damage assessment immediately after the Katrina disaster to compare and contrast hurricane-related damage recorded across the Mississippi landscape. They utilized the same five damage zones that had been created by USFS and SRS. The affected area was divided into five damaged zones. Landfall was at zone one which received the highest damage in contrast to zone five that received the least damage. Stanturf et al. (2007) also mentioned similar damage zones in their study. The data used in the study were the most recently collected by FIA in the study area and widely used with maps of the hurricane storm track. The results showed that of 37,444 trees measured, 7% suffered wind damage; 53% of the damaged trees were hardwoods and 47% were softwood. Except from the zone of greatest impact (zone one), the hardwoods experienced more overall wind-related damage than softwoods. There were differences of damage between the species with the highest damage level at 31% for *Magnolia virginia* L. (sweetbay), and the lowest was 0.4% for *Juniperus virginiana* L. (eastern redcedar). The results from this study estimated that 87% of forested plots in zone one and 44% of forested plots statewide experienced some wind damage. They compared their results with the results obtained from USDA-FIA which indicated damage on 90% of the timberland area in zone one and 37% of timberland statewide. Exposure of forest stands to hurricanes results in loss of high value timber which often creates the need for salvage logging leading to costly forest management (Boutet and Weishampel 2003; Shedd 2006). In addition, broken and uprooted trees in stands can harbor detrimental insects and increase risk of wildfires in the surrounding stands. This justifies the investment in methods that minimize future damage from wind.

The objective of the study by Shedd et al. (2006) was to map downed woody debris from Hurricane Isabel. Hurricane Isabel hit Petersburg National Battlefield, Petersburg, Virginia in September 19, 2003. A map was requested in order to assist in the suppression of wildfire threats and to concentrate salvage logging plans in areas with a high number of downed trees. To address the goal, Shedd et al. (2006) utilized digital aerial photography acquired on March 13, 2004 to map the affected forest stands with Visual Learning System's Feature Analyst. Both, an object-oriented classifier and per-pixel classification were used for identification of downed woody debris. They compared and analyzed which method (per-pixel or object-oriented) was better suited to indicate forest debris across the area. The result from per-pixel classification was not satisfactory because of the inability to distinguish between areas with dead grass fields from areas of downed woody debris. To increase the classification accuracy, training sets for hardwoods and conifers were created. The separate training site shapefiles representing the different species of the downed woody debris were used in a hierarchical approach to automate feature extraction and resulted in improved accuracy of Feature Analyst classification. These classifications were combined using the "combine features" tool. The Feature Analyst classification procedure identified areas of downed woody debris with 90% overall accuracy.

McNab et al. (2006) utilized Ikonos satellite images to detect hardwood canopy damage by ice storm, and tested if the classification accuracy derived from these images depended on spectral band, size of training window, and season of imagery. The study was in the Morehead District of the Daniel Boone National Forest in KY. The major land cover types in the study area were, non-forest land cover consisting of urban related features, and forest land which constituted 80% of the land cover. Agriculture land is not common in this mountainous area. Aerial photographs were taken after the ice storm hit the area and were used to select an area of 1376 hectares to be representative of three different classes: none-to-light damaged forest, moderate-to-heavy damaged forest, and non-forested areas. Sixty plots were selected in each class of canopy damage and non-forested land. Winter and summer Ikonos images were utilized to test four different sizes of classification training windows by expanding the central pixel in the sample plots to test the effects of the window sizes on classification accuracy. The results showed overall accuracy in classification of the three land cover types of land cover ranged from 75% to 38%. Multiple spectral bands tended to create the highest classification accuracy for winter imagery. The highest level of overall accuracy was 74.6 percent, obtained with a combination of three bands (1, 2, and 4) using winter imagery. Single pixels and 3x3 pixel arrays were the most suitable size training areas. The classification accuracy was not significantly affected by the season of imagery; 69% was average accuracy for both winter and summer imagery.

1.1.1.3 Schema Models

Zeng et al. (2004) studied the influence of clear-cutting on the risk of wind damage at forest edges in Central Finland. They integrated a mechanical wind damage model and an airflow model with forest database containing information at the tree, stand and regional levels. Three different stand categories were examined for different wind speed and risk possibility: (Case1) current stand edges with no clear cutting at the edge of the forest, (Case 2) stands with new harvesting edges and have reached the acceptable minimum diameter and/or age, and (Case3) stand age more than 100 years. The mechanical wind damage model HWIND designed by Peltola et al. (1999) was applied to calculate critical wind speed. The regional airflow model Winds Atlas and Application Program (WAsP; Troen and Petersen 1989) was utilized to modify the uniform-terrain wind speed. Site and geographical databases on forest stand parameters were used in the models. Data derived from a meteorological station located about 30 km north of the study area were used to calculate wind speed and direction. The model also incorporated probabilities associated with long term duration in wind speed at the sites. The results from Zeng et al. (2004) showed that new clear cutting (Case2) increases high wind speeds and stands were more susceptible to wind damage at local level. The risk was lower with wind speeds less than 20 m/s as compared to Case1 and Case3, though it increased for critical wind speeds greater than 20 m/s. In general, the mean critical wind speed was between 15 and 30 m/s, depending on the species and case study category. Stands with heights greater than 10 m located adjacent to canopy gaps are at higher risk of wind damage.

1.1.2 Forest Ownership

Land ownership is a key factor in many social-economic and environmental issues, and forest ownerships are particularly complicated and diversified. According to the *Forest Resources of the United States, 2007*, it is estimated that 304 million hectares of forestland are in the United States (Smith et al. 2009). A significant percentage of forestland in the United States has been privately owned by individuals since European settlement. In 2007, more than half of forestland was owned by private individuals, corporations, and other private groups; 171 million hectares or 56 percent of total forest land. Non-Corporate Private Forest (NCPF) owners own 115.3 million hectares or 38 percent of total forestland. NCPF consists of individuals, couples, estates, trusts, nongovernmental organizations, clubs, associations, and other unincorporated groups. Corporate Private Forest (CPF) owners own 56 million hectares or 18 percent of total forestland. The remaining 44 percent, 133 million hectares, of total forestland is publicly owned (Smith et al. 2009). In the last 50 years, the proportion of public ownership remained relatively constant (Smith et al. 2009). The number of forest owners in the United States increased by about 11% between 1993 and 2003 to 10.3 million landowners (Butler and Leatherberry 2004). At the same time there have been no significant increases in forestland area. In the eastern U.S, more than 75 percent of forestland is owned by NCPF. The proportion of these forests near the Atlantic and Gulf coasts are at increasing risk from hurricanes. This ownership pattern has affected forest alteration more than natural disturbances which mainly include wind or fire. Increases in population over time have resulted in minor losses of forestland to urbanization and associated developments. By contrast, parcelization of forests into smaller ownerships has led to social and economic limitations on forest management options. Good forest management requires a thorough knowledge of the resource base and the factors affecting it. Forest owners and their reasons of owning forestland, objectives, expected benefits, harvest experience, and management planning, are essential factors of management (Butler and Leatherberry 2004). To better understand the factors that affect the use and management of forestland, forest ownership needs to be taken into consideration.

According to the *Forest Resources of the United States, 2007*, it was estimated that total forestland area in Mississippi was 7.9 million hectares: - publicly owned forest was 931 thousand hectares and total privately owned forestland was 7 million hectares. NCPF owners owned 5.1 million hectares of the total forested land. CPF owners owned 1.9 million hectares of the total forested land (Smith et al. 2009). In Mississippi, the majority of forestland is privately owned. The private sector controls about 88% of Mississippi forestland. The National Woodland Owner Survey estimated 163,000 forests are family owned in Mississippi. It is estimated 83% of these owners hold tracts of less than 40 hectares with 53% being less than 8 hectares (Oswalt et al. 2009). Thorne and Sundquist (2001) proved that timber harvesting costs per unit area increase as the size of landholdings decreases. This fact assumes only 29,000 (17%) of Mississippi's 163,000 private family forestland owners are likely to reasonably consider their forestlands to be available for timber harvesting and subsequent large-scale regeneration (Oswalt et al. 2009).

Butler and Leatherberry (2004) concluded that owners of smaller parcels are less active forest managers than owners of larger tracts regardless of whether they are managing their land for timber production or natural protection. Forest owner objectives and attitude toward risk must be considered when strategies for disturbance regime are integrated in forest management (Stanturf et. al. 2007). In contrast to NCPF, public forest and large forestland should have the opportunity to pursue management that includes plans to mitigate large-scale natural disaster such as hurricanes. Legal restrictions limit the manipulation of public forest over large areas, and therefore limit efforts to surpass large infrequent disturbances (Stanturf et. al. 2007).

Smaller forest tracts tend to be more fragmented by non-forest development. Therefore, such tracts are not easily managed for forest habitat and watershed values. Since NCPF land tends to be highly fragmented compared to the CPF and publicly owned forests, management practices and harvesting behavior within NCPF land differs from the other ownership groups. Classification of different forestland ownership according to fragmentation could help understand the effect of different ownership and their different management behavior on forestland susceptibility to wind damage. There is a need to provide timely information about forest hurricane damage to managers and decision makers. Forest damage information derived from classified remotely sensed data may provide a more real-world representation of forest change of forested areas after disturbance event, which can help managers to develop future management plans.

1.1.3 Forest Classification

Forest land managers use classification to segregate land into subdivisions (landtypes) based on similar characteristics. In the past, forest land classifications have been manually created. The classification accuracy often depends on the experience of the classifier. The overall objective of Wang et al. (2006) was to determine the possibility of classifying forest land using a GIS and remotely sensed data. Statistical modeling approaches were used to test the regularity of map classification produced by computer with the base map that was developed manually by an expert on forest land classification for an area of the Mid-Cumberland Plateau focused on Jackson County of northern Alabama. The Isoclustering method used to classify land types was compared with Smalley's (1982) classification. The Isocluster algorithm is an iterative process for computing the minimum Euclidean distance when assigning each candidate cell to a cluster. Smalley (1982) classified and evaluated forest sites for the management of commercially valuable tree species. His evaluation was based on ecology, soils, site features, and yields and often extrapolated from adjacent regions. Five variables were utilized in the Wang et al. (2006) classification: elevation, slope, aspect, soil texture, and soil types using the Spatial Analyst feature in ArcGIS. The results from Wang et al. (2006) illustrated the landscape fragmented based on these classifications, and the boundaries of land type polygons were difficult to define compared to Smalley's (1982) work. This fragmentation was caused by the Isoclustering procedure which divided the land into different classes without supervision. Some agreement between Isoclustering classes and Smalley's land type were found in the study area, but the overall agreement was low based on the visual assessment. Wang et al., (2006) suggested Isoclustering can be applied to large areas to separate land subjectively and turn out classifications quickly.

Whereas previous studies (Gresham et al. 1991, Savill 1983; Miller et al. 1987) have considered the effects of tree morphological characteristics including tree height, crown, leaf shape, and density on resistance to wind damage, none have assessed the relationship between forest age diversity, forest type diversity and forest ownership types with forest damage. Stanturf et al. (2007) assessed the impacts of Hurricane Katrina on coastal forests in the Gulf of Mexico using forest inventory data. Many studies conducted in Mississippi generally used forest inventory data at stand level (for example Oswalt and Oswalt, 2008) to assess forest vulnerability to wind catastrophes. Nonetheless, in this research remotely sensed data at landscape level was used which is considered more economical and easy to analyze after hurricane events. Variations according to forest ownership types were not explored in previous studies. This study has undertaken possible approaches that have not been examined for hurricane impacts in the SE before. The variables forest age diversity, forest type diversity and forest ownership were considered in order to improve the overall understanding of impacts of hurricanes in the SE.

1.2 Objectives

The primary objective in this study was to examine how the disturbance by Hurricane Katrina was influenced by forest fragmentation based on different forest ownership groups (NCPF, CPF, public forest). In the context of Mississippi, there are various forest ownership types which are connected over large regions. However, forest fragmentation is ubiquitous resulting in increased amount of forest edges. Higher incidence of forest edges leads to greater risk of wind damage particularly in areas that have been clear cut or intensively thinned. Since the structure and functioning of forests are greatly affected by severe winds, hurricane damage entails significant economic losses for landowners. Forest management practices related to tree species, tree height, tree diameter, crown area, tree age, stand density, and edge-to-area ratio are controlled by landowner's goals (Bieling 2004). These have important effects on susceptibility of forests to wind damage. The secondary objective was to examine the influence of forest age diversity, forest type diversity and rainfall on forest change due to wind damage. Consequently, we must understand the responses of forest to wind damage by the different forest ownership groups to provide information for better management practices. This study used moderate resolution imaging spectroradiometer (MODIS) normalized difference vegetation index (NDVI) change products to indicate the intensity of damage by forest fragmentation as well as different forest ownership types. MODIS products were used as an integral component of a Research Opportunities for Space and Earth Science (ROSES) project funded by NASA that focused on the impact of post-hurricane Katrina on forest management practices[1].

1.3 Hypotheses

The hypothetical proposition was that the MODIS change products represented likely canopy alteration and therefore a potential surrogate to damage. MIFI data were used to characterize damage with respect to forest ownership types. This study also used both high resolution imagery and MODIS products to categorize susceptibility of forestland owned by NCPF, CPF, and public forest to Hurricane Katrina damage within the study area. Various processing techniques of both high resolution and MODIS imagery provided a means to investigate forest susceptibility to wind damage. This

[1]Radiance Technology. 2012. ROSES 2008 Project: Improving post-Hurricane Katrina forest management with MODIS time series products. Final report to NASA 67p.)

information was utilized to map forestland showing susceptibility to wind damage in contiguous patches and assumed management. The hypotheses examined were:

- Forestland owned by NCPF is more susceptible to wind damage (assumed represented by NDVI percent change) than CPF and public forest because they are highly fragmented and have different management practices.
- Forest age diversity is negatively associated with NDVI percent change.
- There is a positive relationship between forest type diversity and NDVI percent change.
- Higher rainfall amount is positively associated with NDVI percent change.

CHAPTER II

METHODS

2.1 Study Area

The study covered 1.5 million hectares, focusing on the southeast part of Mississippi namely Forrest, George, Greene, Hancock, Harrison, Jackson, Lamar, Pearl River, Perry, and Stone Counties (Figure 2.1). These counties were selected because of severe damage caused by Hurricane Katrina. The area of forestland was approximately 1.2 million hectares or 75.6 percent of the study area, comprised of 67.5 percent pine forest, 14.0 percent hardwood, 8.2 percent mixed pine-hardwood and 10.0 percent regeneration (MIFI 2006). Regeneration accounted for about 119 thousand hectares.

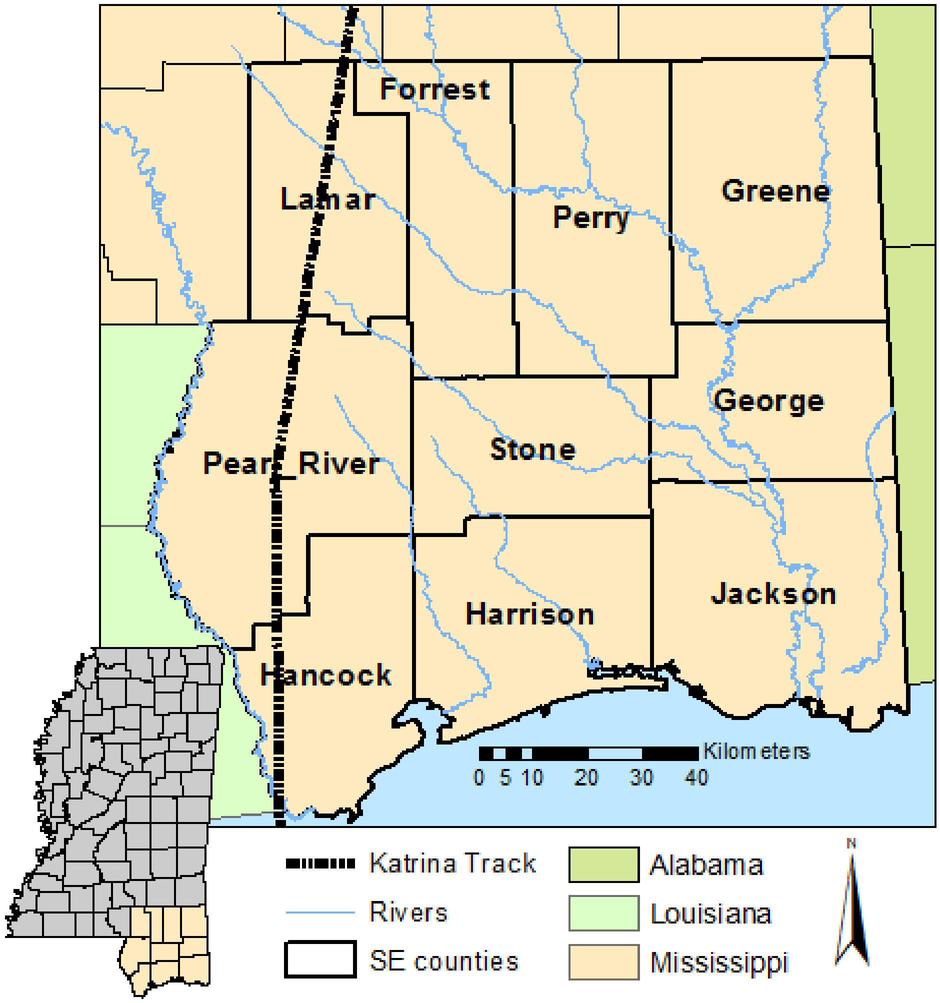


Figure 2.1 The ten-county study area in southeast Mississippi, USA.

Hurricane Katrina track were acquired from the Mississippi Automated Resource Information System (MARIS); Boundary and river locations were derived from the United States Census Bureau (USCB)

2.2 Data

Data in this study were obtained from two main sources: "ROSES 2008 Project: Improving Post-Hurricane Katrina Forest Management with MODIS Time Series

Products,"[2] and MIFI. Temporally processed MOD13 NDVI products were accessed from Radiance Technologies Incorporated (RTI) in collaboration with Forest and Wildlife Research Center (FWRC), Mississippi State University (MSU).

2.2.1 MODIS-NDVI products

The MODIS sensor generates satellite imagery characterized by 36 spectral bands ranging from 0.405 to 14.385 nm: - bands 1 and 2 have 250m spatial resolution while bands 3 to 7 have 500m spatial resolution. The main function of these seven spectral bands is to facilitate remote sensing of land surfaces and land cover mapping (Friedl et al. 2002).

MOD13 NDVI products were used by the ROSES project to produce maps illustrating NDVI percent change in forest greenness between pre-hurricane and post-hurricane time phases. The pre-hurricane Katrina period represented the baseline that was defined from August of 2003 and 2004. A merging process was performed to select maximum NDVI values to create the baseline product. The post-hurricane period considered August of 2005 and therefore, characterized the extent of disturbance attributed to Hurricane Katrina on Mississippi forests. Whereas the ROSES project was conducted on the MIFI Southeast Inventory District (SID), the current study only covered 10 counties in the MIFI-SID.

The NDVI products were used to develop Cumulative Integral (CI) NDVI products. The "NDVI CI product is an integrated "accumulation" of the composite 16-

[2] Radiance Technology. 2012. ROSES 2008 Project: Improving post-Hurricane Katrina forest management with MODIS time series products. Final report to NASA 67p.

day MODIS NDVI measurements from the beginning through a user-specified end date of the calendar year"[3]. Each year was characterized by 22 cumulative integral intervals based on 16-day composites. This study considered NDVI for the pre- and post-hurricane Katrina periods. NDVI is the normalized ratio between the near-infrared and red regions of the electromagnetic spectrum. NDVI is defined as:

$$NDVI = (NIR - Red) / (NIR + Red) \tag{2.1}$$

where:

NIR represents the near infrared wavelength reflectance value and Red represents the red wavelength reflectance value.

To observe the Hurricane Katrina damage just after landfall, an NDVI Window was extracted from the CI dataset. The NDVI Window 15 period of interest was from August 29 to September 13 and coincided with the occurrence of Hurricane Katrina landfall. The formula for a 16 day NDVI Window extraction is:

$$\text{NDVI Window (Year, Interval)} = \text{CI(Year, Interval)} - \text{CI(Year, Interval}-1) \tag{2.2}$$

where:

CI (Year, Interval) = the cumulative integral value for the indicated year through the indicated cumulative integral interval.

NDVI percent change products were produced by RTI and described as follows:

Baseline = Maximum of the NDVI Window 15 values from 2003-2004

Post = NDVI Window 15 values from 2005

[3] Radiance Technology. 2012. ROSES 2008 Project: Improving post-Hurricane Katrina forest management with MODIS time series products. Final report to NASA 67p.

Then NDVI percent change is defined as:

$$\text{NDVI Percent Change} = (\text{Post 2005} - \text{Baseline 2003-2004}) / \text{Baseline 2003-2004}) * 100 \qquad (2.3)$$

The NDVI percent change produced by Equation 2.3 had values ranging from negative 100 to positive 100. Several masks were applied to exclude recently harvested forest areas before the Katrina event as well as non-forest areas. Non-forest areas were masked using the 2006 MIFI forest type map, forestland was assigned a value of one and non-forest area to zero thereby helping to improve precision of products because some areas which experienced changes in forest cover not attributed to Hurricane Katrina (such as harvested areas after the baseline) were not considered in the analysis. The continuous, masked NDVI percent change image was recoded in ERDAS Imagine into a six class thematic forest disturbance map. The six MODIS NDVI change classes which were highlighted in the ROSES Project were applied to assess forest disturbance relative to baseline NDVI values. Class 1 was defined as (<=0%), class 2 (>0 to 5%), class 3 (>5 to 10%), class 4 (>10 to 15%), class 5 (>15 to 20%) and class 6 (>20 %). These classes indicate the range of percent decreases in the NDVI between the pre- and post-hurricane Katrina periods. Thus canopy relative vigor decreased from Class 1 to Class 6.

2.2.2 Landsat Forest Age and Type Thematic Maps

Two thematic maps were obtained from MIFI depicting forest age and forest types. These thematic maps were created using Landsat leaf-on and leaf-off images (Collins, et al. 2005). Leaf-on classification resulted in three classes: water, forest and non-forest. The resultant map was used to mask leaf-off image of the same period to discriminate pine, hardwood and mixed pine-hardwood forest types. Forest age was generated from several leaf-on images taken at 5-year intervals and each year's set was independently classified by a post-classification procedure to forest and non-forest. Post-classification is sometimes called map-to-map comparison and it entails comparing separately classified images taken from different times (Serra, et al. 2003). A number of thematic maps reflecting forest and non-forest areas were used to label each forested cell with respect to the most current layer. By comparing consecutive layers, forest cells that were observed as a non-forest can labelled as forest regeneration (Collins, et al. 2005). In the event that area was continuously forested in all data sets, it was considered older than 33 years.

2.2.3 Data Sources

The study database includes precipitation, forest ownership, distance from Hurricane Katrina's track, and distance from gulf coast. The monthly cumulative precipitation of August 2005 was derived from the National Weather Service (NWS). The data used is for monthly rainfall precipitation is estimated at 24-hour Hydrologic Rainfall Analysis Project (HRAP) grid cell. The ownership map was downloaded from United States Department of Agriculture (USDA) Forest Service (USDA). This study employed Hurricane Katrina storm path obtained from Mississippi Automated Resource Information System (MARIS) and the gulf coastline was derived from the southeast border of county maps obtained from the United States Census Bureau (USCB).

2.2.4 Data Preparation

With any GIS information taken from various sources, it is always recommended to set all information to the same uniform standard. This includes changing projection and datum specifications to match across all information being used. Standardizing the different map layers facilitates a precise and efficient analysis.

2.2.4.1 Projection

MODIS NDVI disturbance products were received in the Lambert Azimuthal Equal-area map projection. Using ERDAS and ArcGIS, the disturbance thematic maps were re-projected to Mississippi Transverse Mercator (MSTM) projection based on the, North American Datum 1983 (NAD_1983). Landsat forest type thematic maps of 2003-2004 were used as the baseline and a 2nd degree polynomial was applied with a root mean square error of less than one cell for all maps with nearest neighbor as the re-sampling method.

2.2.4.2 Delineation of Areas of Interest

To delineate the study area boundary, a state level shapefile including the boundaries for the 10 counties of interest was downloaded from USCB. ArcGIS was employed to create the study area boundary and the thematic maps were extracted from this boundary. This process was applied to the forest type, forest age and NDVI percent change datasets.

2.2.4.3 Data Resampling

MODIS and Landsat products have different spatial resolution. MODIS had a 250 meter (m) spatial resolution while Landsat had a 30 m spatial resolution. These dimensions were problematic since they produced misalignment of cells. It was therefore necessary to change cell dimensions of MODIS to 240 m spatial resolution. In ArcGIS, the resample function under Data Management Tool was employed to alter the cell size of MODIS product, using a nearest neighbor resampling routine, the output image composed of 240 m x 240 m cell, with a root mean square error of less than half cell. To fit the Landsat 30 m cells within the 240m MODIS cell without any misalignment or overlapping, a shift function in ArcGIS was used to move the MODIS NDVI percent change image 15 m west and 15 m south. A total of 64 (8 x 8) Landsat 30 m cells fit in one 240 m x 240 m MODIS cell. Figures 2.2 (a) and (b) indicate how the 30 m cells were re-positioned within each 240 m cell.

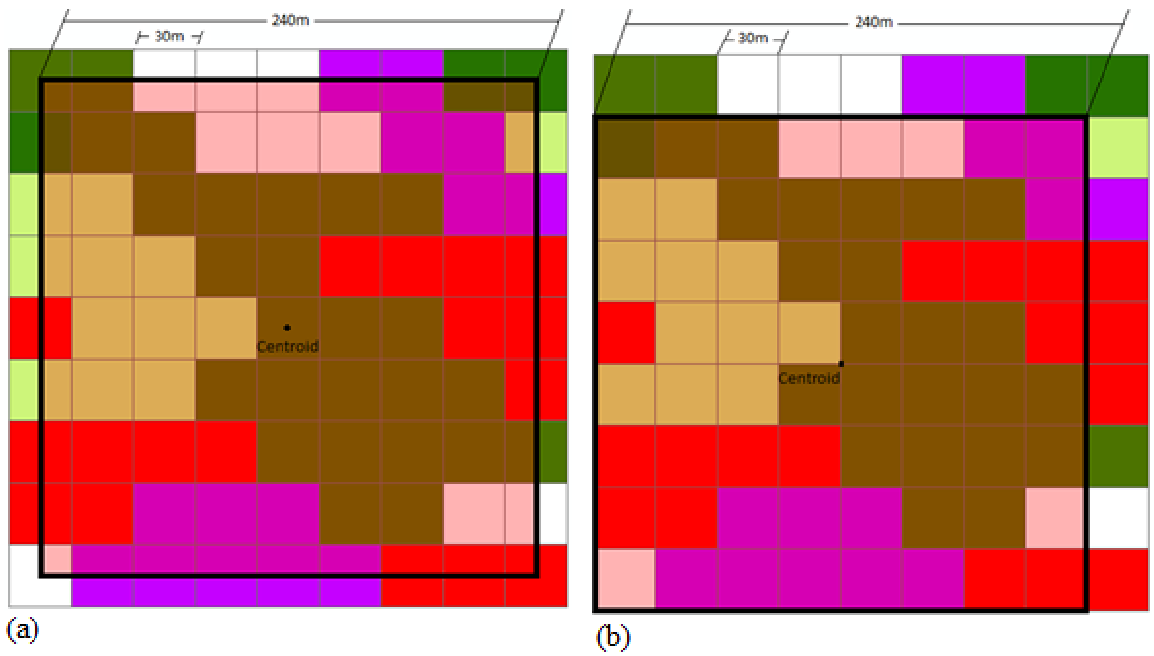


Figure 2.2 Adjusting the misalignment/overlapping between the 64 Landsat 30 m cells and the 240m MODIS cell.

(a) Misalignment between 240 m cell and 30 m cells, (b) 64 30 m cells completely within the 240 m cell. Colors represent different forest types.

2.2.4.4 Map Masking

Since forest age and forest type data sets were based on Landsat 30 m x 30 m spatial resolution and NDVI present change data were based on MODIS 240 m x 240 m spatial resolution, the discrepancy in cell resolution between MODIS and Landsat products necessitated the use of a mask to ensure that the different layers were matched. A mask was created from MODIS data to mask forest age and forest type Landsat based thematic maps, a value of zero was assigned for non-forest areas and a value of one was ascribed to forest areas. As a result, the final products only included forest age and forest types that were aligned with the appropriate NDVI change.

2.2.4.5 Map Re-coding

The thematic maps obtained from RTI and MIFI were re-coded. The NDVI percent change map originally had six classes, the forest age thematic map had thirty five classes, and forest type thematic map initially had six forest types. The NDVI percent change map was re-coded to three classes named positive change, moderate negative change and high negative change. The original classes 1 and 2 were re-coded to positive change class, classes 3 and 4 to moderate negative change while classes 5 and 6 were combined to high negative percent change class. The MIFI age dataset was re-coded as follows: forest existing before 1972 to class 10, forest existing from 1972 through 1983 to class 20, forest existing from 1984 through 1994 to class 30, forest existing from 1995 through 2005 to class 40, areas with forest regeneration were assigned to class 50 and non-forest, water and agriculture were combined to class 60. The MIFI forest type and regeneration map initially had six forest type classes: pine, hardwood, mixed pine-hardwood, pine regeneration, hardwood regeneration and mixed hardwood-pine regeneration. The pine forests class was re-coded to class 100, hardwood to class 200, mixed pine-hardwoods to class 300 and non-forest area to class 500. Pine, hardwood and mixed regeneration classes were merged into class 400 because they account for a relatively small percent of the whole study area (10%) and also they have similar conditions and structural characteristics.

The recoded thematic maps forest age, forest type, and NDVI percent change were converted into text files using shell, awk and python programming languages to facilitate statistical analysis. Areas outside the study site were designated by a value of zero and ultimately discarded. The NDVI percent change text file was used together with forest age text file to produce a matrix showing the frequency of forest age classes associated with NDVI percent change in each 240 m cell. Similarly, NDVI percent change text file was used in conjunction with forest type text file resulting in another matrix indicating frequency of different forest type classes related to NDVI percent change.

In the above step, the datasets were processed at the individual cell level to determine the frequencies of different forest age and forest type classes within each cell of MODIS-NDVI percent change (Figure 2.3).

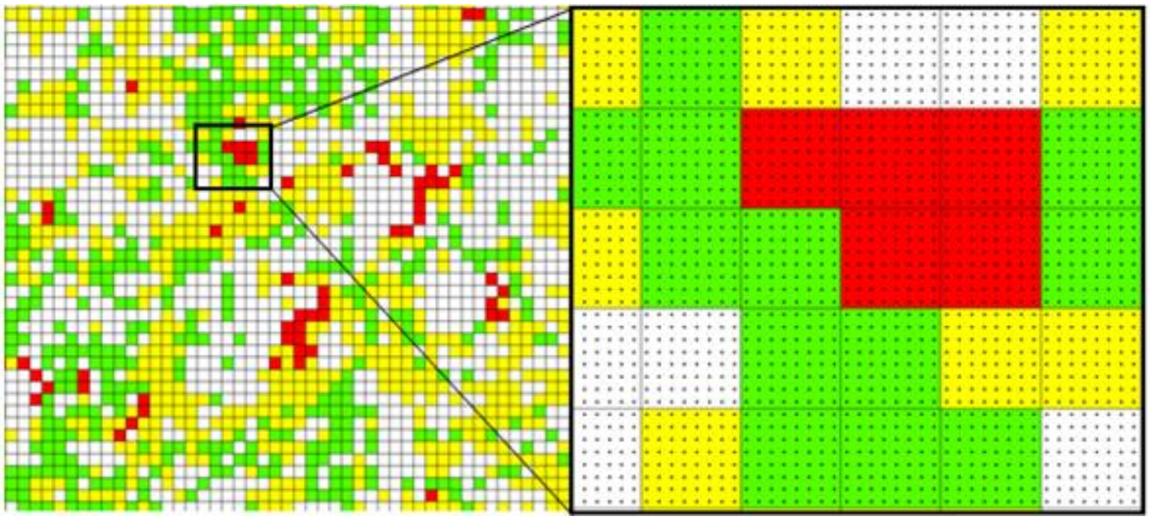


Figure 2.3 Cell level dataset showing each MODIS-NDVI percent change cell including 64 values of 30 m.

Landsat derived products with the individual dots representing the center of 30 m cells. Red = High negative NDVI % change, Yellow = Moderate negative NDVI % change, Green = positive NDVI % change.

2.2.4.6 Distance Maps

A priori, the impact of Hurricane Katrina on forest was expected to decline with the increase of distance from the hurricane track. Also, increasing distance from the gulf coast would result in a dampened effect of damage severity. Oswalt and Oswalt (2008) found that as distance from landfall increased wind damage decreased. In ArcGIS, the distance function found under Spatial Analyst Tools was used to create two maps indicating distance from Hurricane Katrina track and distance from Mississippi Gulf Coast.

Distance variables were calculated using the Hurricane Katrina path obtained from MARIS and the Mississippi Gulf Coast shapefiles (USCB). The resulting maps with 240m cell size were used to make a distance variable showing the combined effect of distance from hurricane track and coastline. The distance maps from the Hurricane

Katrina path and the Mississippi Gulf coast were employed in a simple additive weighting model producing a map demonstrating distance from Katrina track and Gulf coast. The model was calculated in the ArcGIS raster calculator as follows:

$$\text{model\_weight equation} = 0.6 * (1 - ([\text{dist\_to\_track}] / 136043)) + 0.4 * (1 - ([\text{dist\_to\_coast}] / 143529)) \tag{2.3}$$

where: 136043 represent hurricane track length in meters within the study area.

143529 represent coast line length in meters within the study area

This equation assigned weighted values to variables based on a number of ideals taken from knowledge of environmental and geographical behaviors. It is known that distance from storm track has more effect on damage severity than distance from the coast, therefore a higher weight is given to distance from track. The primary objective of creating the distance map was to partition the study into homogeneous zones based on the distance from storm track and coastline. The distance grid was classified into five different distance zones for more robust estimation of the regression modeling within each zone (Figure 2.4).

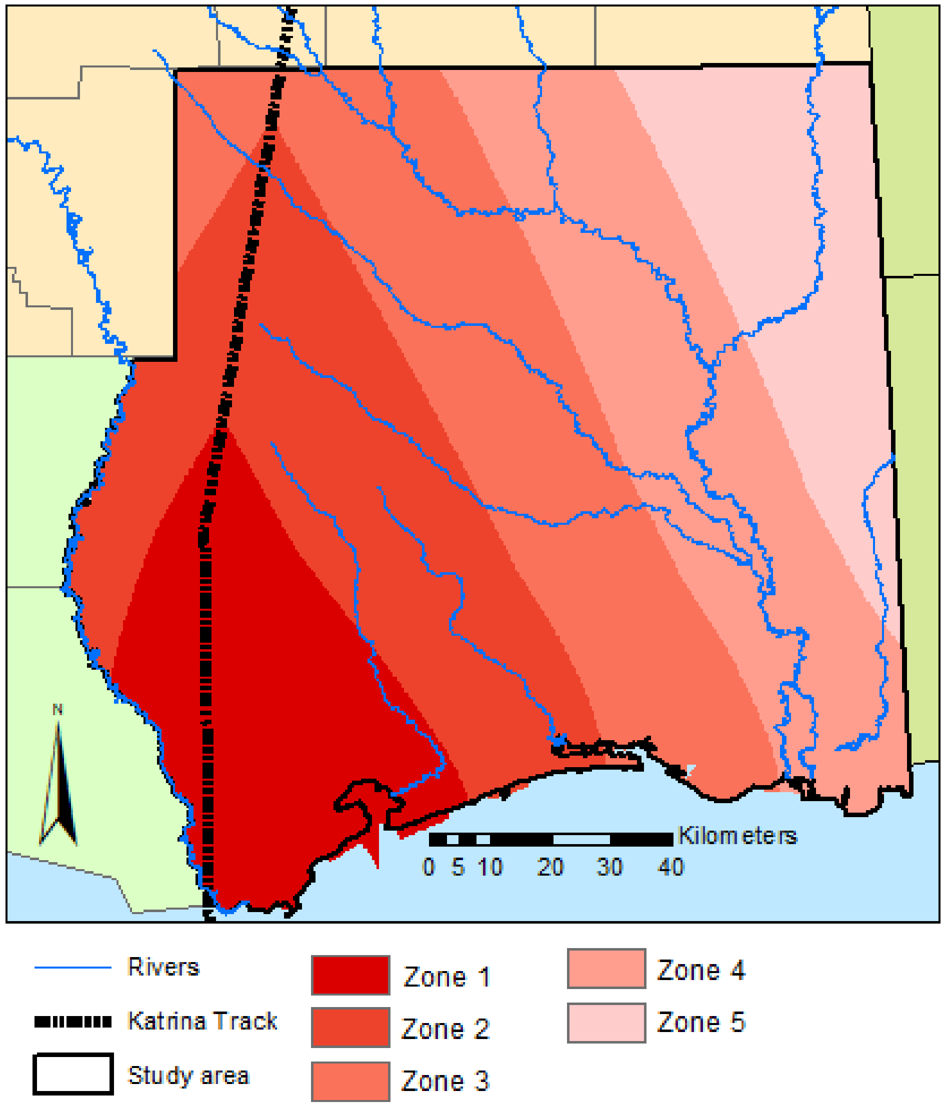


Figure 2.4 Weighted distance zone map for the study area.

The map created based on Hurricane Katrina track and distance from Mississippi Gulf Coast. Hurricane track was acquired from the Mississippi Automated Resource Information System (MARIS); boundary and river locations were acquired from the United States Census Bureau (USCB).

2.2.4.7 NDVI Percent Change

Areas with positive NDVI percent change values represent an increase in overall vegetation greenness. In forests with significant overstory impacts from the hurricane, it is likely evergreen vegetation in middle and understory may have been exposed, therefore, greater NDVI values are obtained. Damaged forest was assumed to be represented by negative NDVI percent change values hence positive values were removed from dataset. Figure 2.5 illustrates the forest hurricane disturbance product, based on percent change of the NDVI values between 2005 and 2003-2004 baseline. The green color represents areas that had no NDVI percent change or had positive change in forest canopy greenness. The yellow color represents a moderate NDVI percent change of forest canopy greenness and the red color represents very high NDVI percent change in forest canopy greenness. The yellow and red color shows only areas that had negative change values that were employed and which appear to be more frequent in areas of coastal, river estuary and closer to storm path.

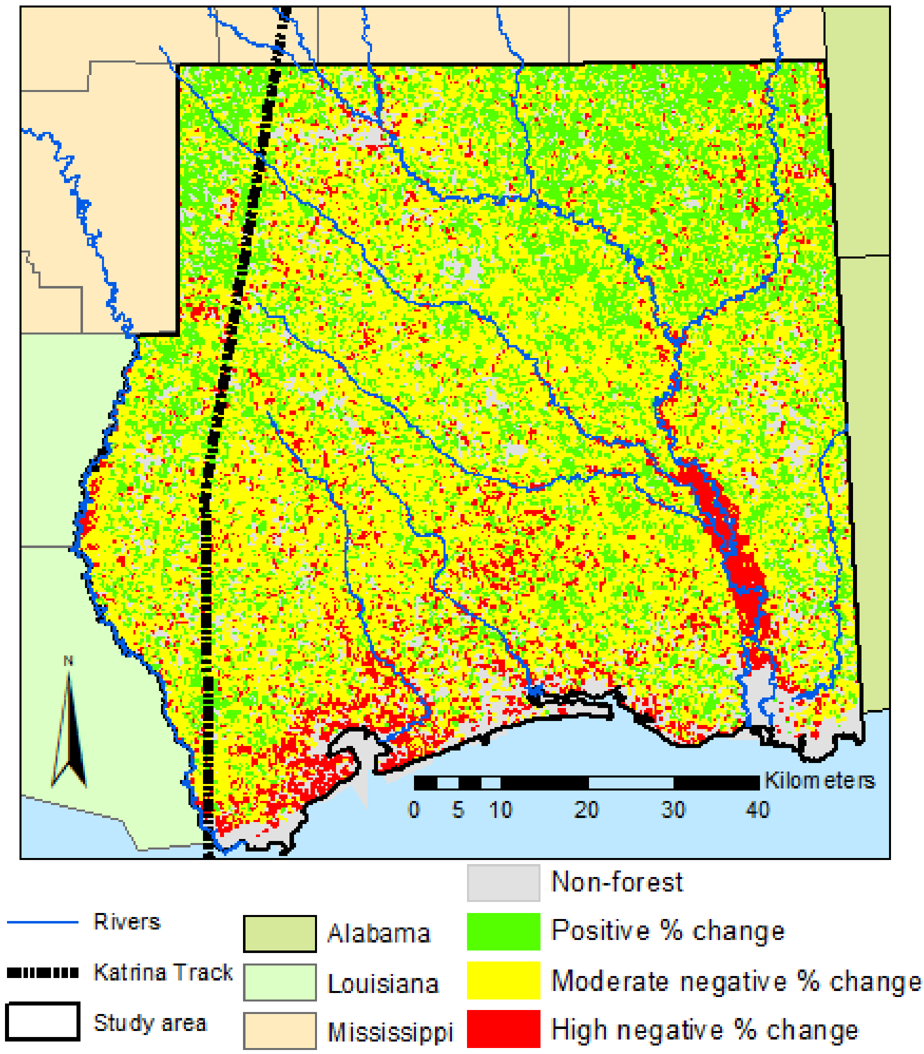


Figure 2.5 Normalized difference vegetation index (NDVI) percent change map.

Hurricane track were acquired from the Mississippi Automated Resource Information System; Boundary and river locations was acquired from the United States Census Bureau; Change data derived from Radiance Technologies Institute.

The NDVI change classes were recoded to a binary variable of 0/1 where 0 = low NDVI percent changes (assumed no damage) and 1 = high NDVI percent changes. Two classification techniques were used: Natural breaks (NB) versus thresholds percent change classes originally derived from RTI classes. The NB was derived from NDVI percent change histogram and the three different thresholds used in the binomial logistic regression models. The three percent change thresholds of 10, 15 and 20 were examined and created from RTI. These thresholds were chosen in reference to the ROSES Project classification, which was defined at 5% intervals. In the histogram (Figure 2.6) the NDVI percent change data is left skewed and is concentrated in the lower 20%. This means threshold values equal to and less than 10 were given a value of zero (low NDVI percent change) and values greater than 10 were given value of one (high NDVI percent change). The same can be said for 15 and 20 thresholds. For the NB classification, values equal to and less than 8.23 were given a value of zero (low NDVI percent change) and values greater than 8.23 were given a value of one (high NDVI percent change).

In order to assess the impact of Hurricane Katrina on existing forest cover, NDVI percent change was used. However the NDVI percent change variable was expressed as continuous and categorical variables. The mean NDVI percent change was 8.8 with a standard deviation of 5.5. Nevertheless, the distribution of this variable was skewed to the right with a few extreme values as depicted in Figure 2.6. For instance the minimum and maximum values were 1.1 and 77 respectively. The six MODIS NDVI change classes which were highlighted in the ROSES Project were applied to assess forest disturbance relative to baseline NDVI values. Class 1 was defined as (<=0%), class 2 (>0 to 5%), class 3 (>5 to 10%), class 4 (>10 to 15%), class 5 (>15 to 20%) and class 6 (>20 %). These classes indicate the range of percent decreases in the NDVI between the pre- and post-hurricane Katrina periods. Thus canopy relative vigor decreased from Class 1 to Class 6.

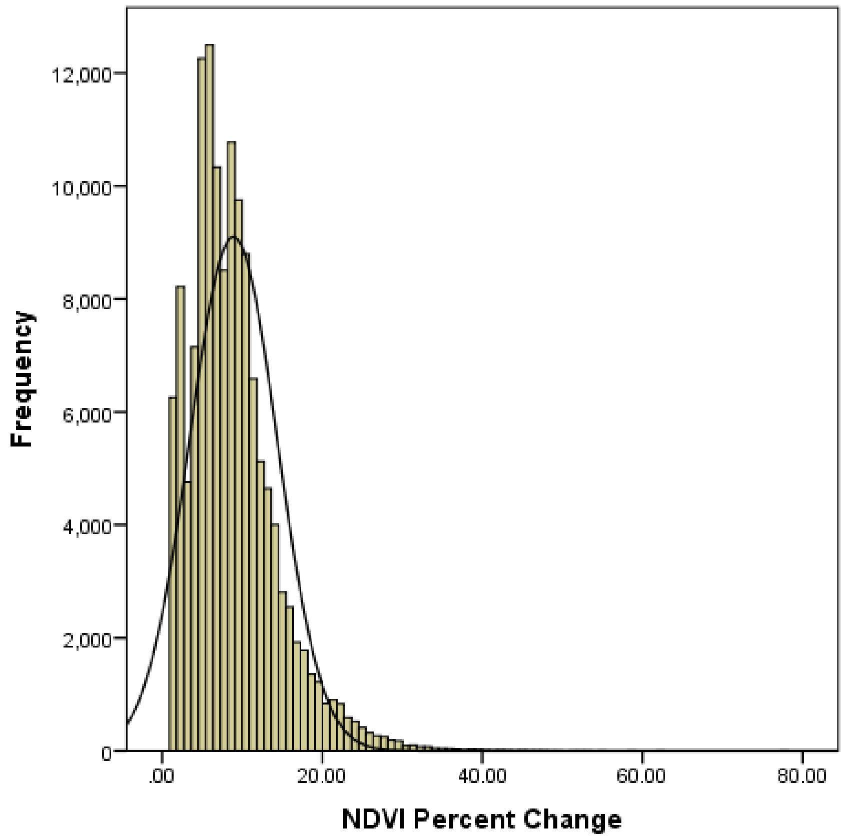


Figure 2.6 Normalized difference vegetation index (NDVI) percent change distribution within southeast Mississippi.

Change data derived from Radiance Technologies Institute.

About 62% of the forest land experienced moderate assumed damage as reflected by the NDVI percent change. However, about 11% of the area was categorized as high negative NDVI percent change with 15644 cells within this severity range. On the other hand, approximately 27% of the forest land was characterized by positive NDVI percent change (Figure 2.7).

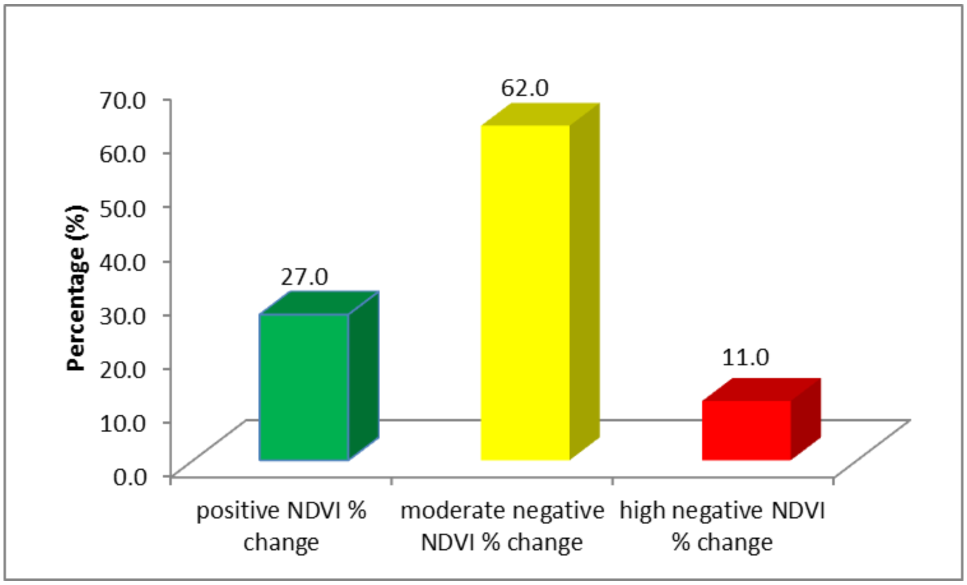


Figure 2.7 Proportions of normalized difference vegetation index (NDVI) change classes in the study area.

Change data derived from Radiance Technologies Institute[4].

2.2.4.8 Forest Age

Initially, the forest age thematic map obtained from MIFI showed age on an annual basis from 1972 to 2006. An age variable was created indicating 10 year intervals. This was done from the viewpoint of different forest products that can be represented by age (tree size). For example pine stands less than 11 years old generally correspond to pre-commercial trees, stands between 11 and 21 years old correspond to pole timber, stands between 22 and 33 years old correspond to chip and saw timber, and stands greater than 33 years old correspond to very large diameter timber. The forest age thematic map is shown in Figure 2.8.

[4] Radiance Technology. 2012. ROSES 2008 Project: Improving post-Hurricane Katrina forest management with MODIS time series products. Final report to NASA 67p.

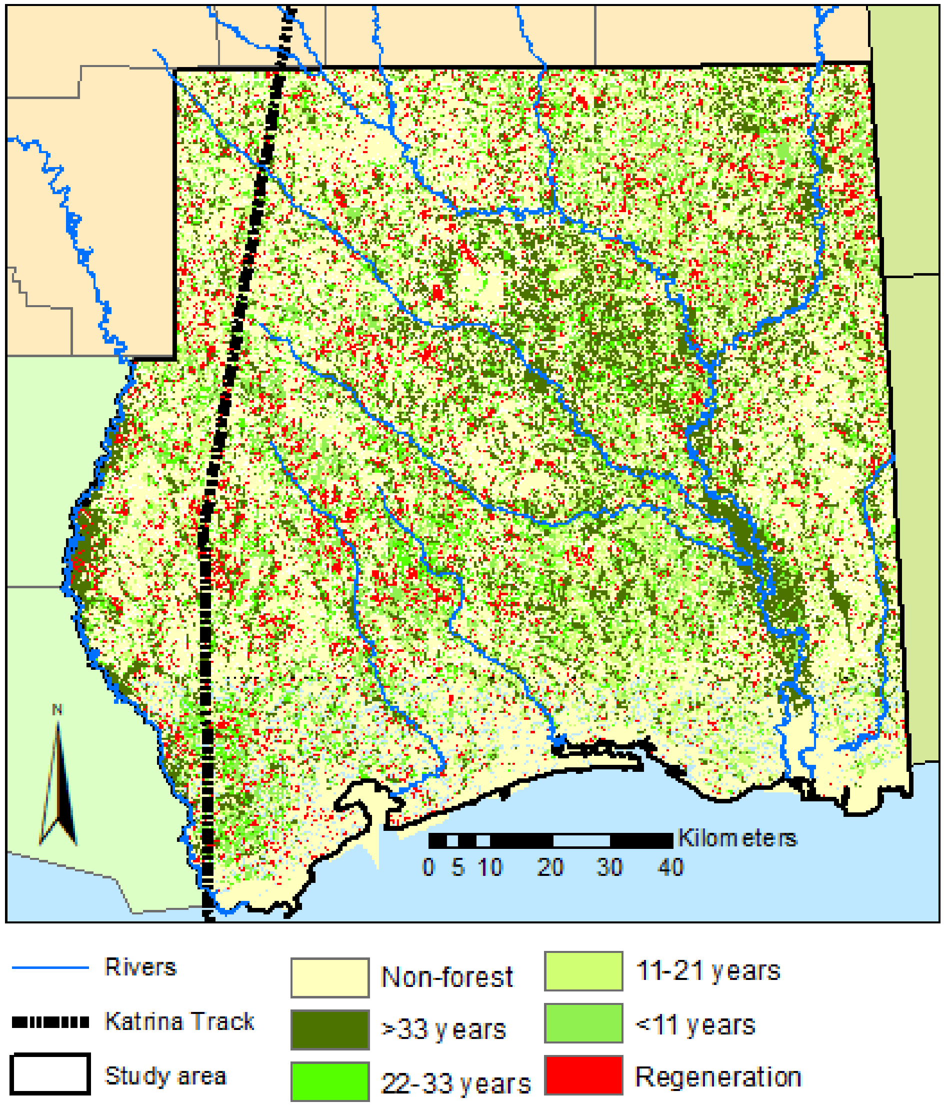


Figure 2.8 Forest age map showing five age classes.

Hurricane Katrina track was acquired from the Mississippi Automated Resource Information System; boundary and river locations were acquired from the United States Census Bureau; forest age was derived from Mississippi Institute of Forest Inventory.

Figure 2.9 indicates the distribution of age of forest stands in the study area. It can be observed that the highest proportion of forest land area was in the form of mature stands greater than 33 years old (28.8%) whereas forests aged between 22 to 33 years old represented 10.0% of the total forest area. However, younger forests between 11 to 21 years old were also prevalent representing 17%. Forest stands less than 11 years old accounted for similar proportion (17%). The area covered by regenerating forests was 13% and the remaining 14% was classified as non-forest.

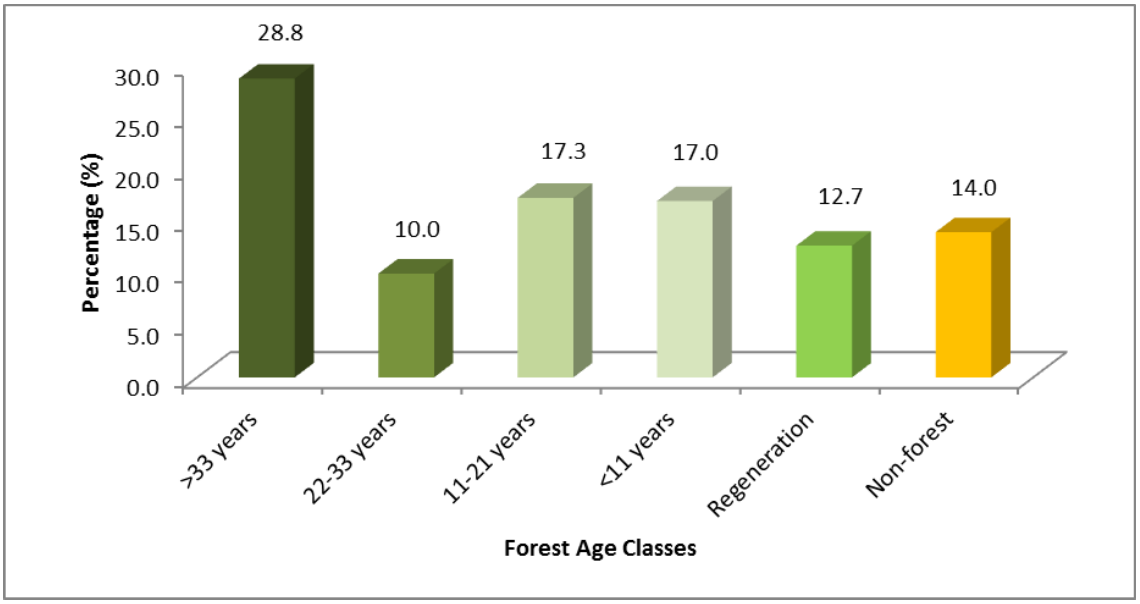


Figure 2.9 Forest age distribution.

Forest age data was derived from Mississippi Institute of Forest Inventory.

2.2.4.9 Forest Type

Forest type thematic map (Figure 2.10) was received from MIFI initially with six forest type classes. For the purpose of this study these classes were recoded into four: - pine, hardwood, mixed pine-hardwood and regeneration. Figure 2.10 illustrates the distribution of forest types.

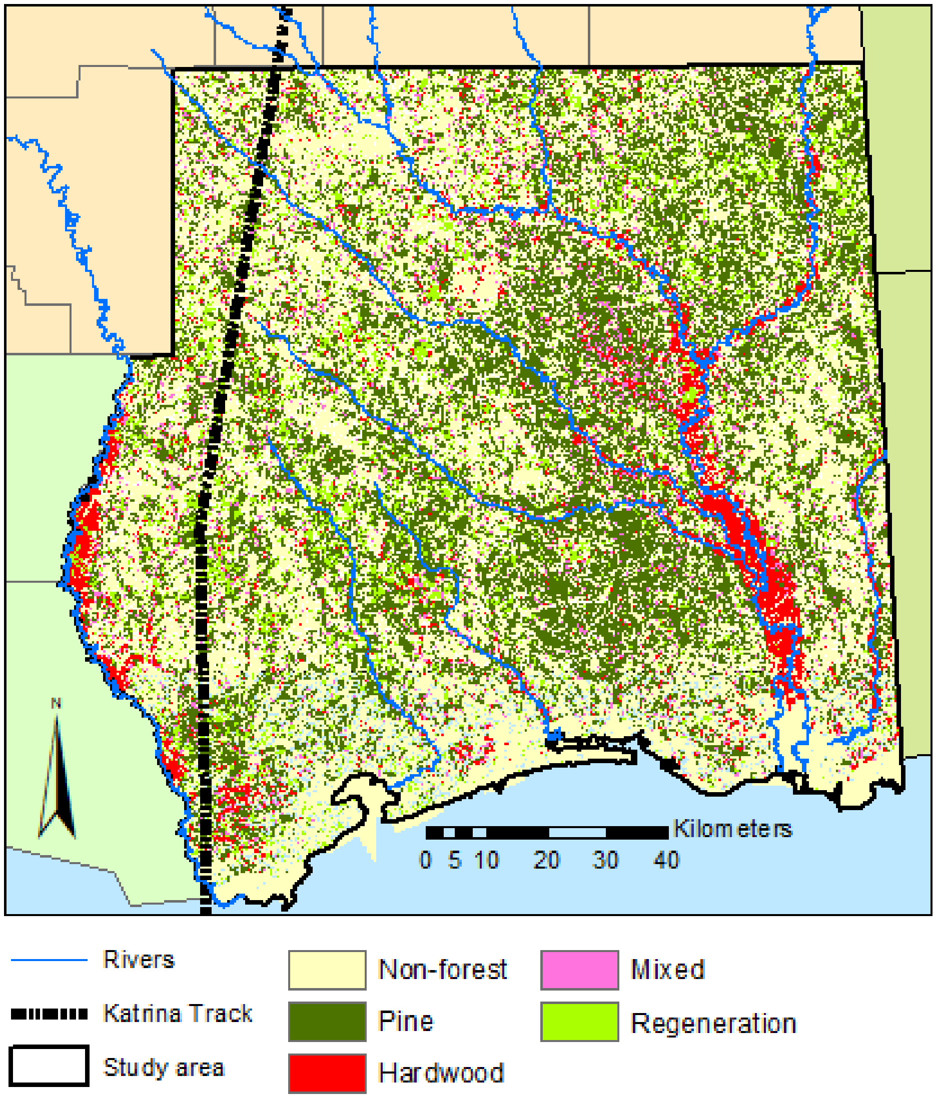


Figure 2.10 Forest type map.

Hurricane track was acquired from the Mississippi Automated Resource Information System; Boundary and river locations were acquired from the United States Census Bureau; Forest type was derived from Mississippi Institute of Forest Inventory.

Forest types were classified into five classes including pine, hardwood, mixed pine-hardwood, regeneration and non-forest areas. Forestland was dominated by pine, which occupied 55.8%, of the study area, the hardwood covers 10.5% and regeneration

12.7%. Mixed forests accounted for a lesser percentage (7.0%) whereas the non-forest class occupied the remaining 14.0% (Figure 2.11).

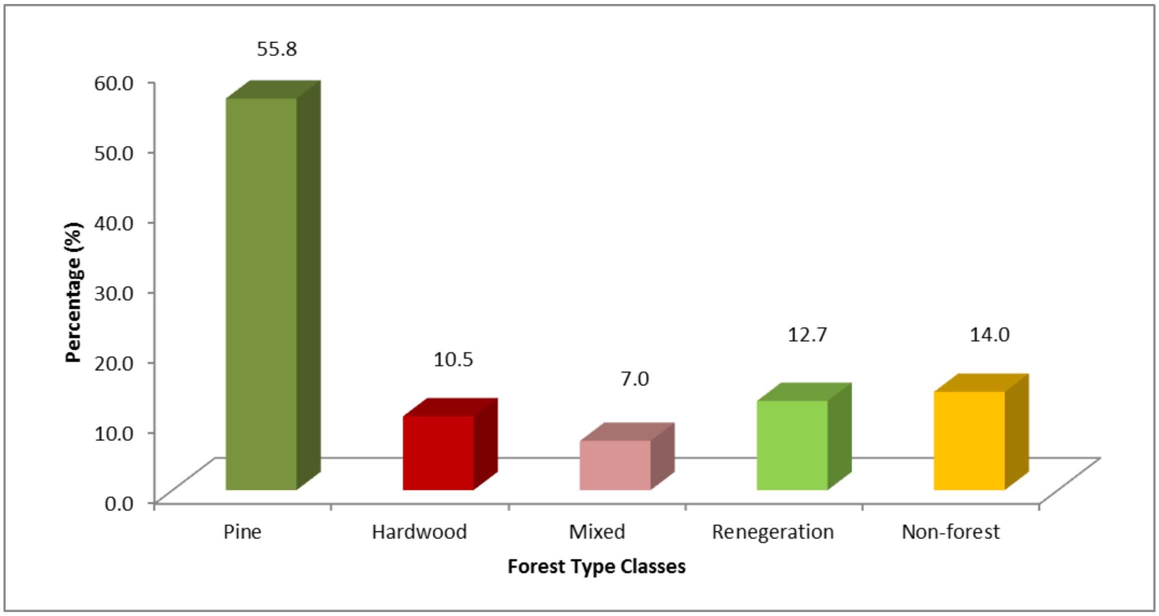


Figure 2.11 Forest type distribution.

Forest type data was derived from Mississippi Institute of Forest Inventory.

2.2.4.10 Shannon-Weaver index

The variable forest age was initially classified into six age classes indicating the relative proportions of each class within each 240 m x 240 m MODIS cell. Similarly, forest types were initially defined in such a way that they were five forest type classes showing the relative percentage for each category within each 240 m x 240 m MODIS cell. The six forest age and the five forest type classes are in categorical form. To use these variables in linear regression, they would need to be in a continuous form. In order to produce a continuous variable, it was therefore expedient to compute Shannon-Weaver indices for forest age, and forest type variables. Essentially, the Shannon-Weaver diversity index has been used to document tree species diversity and thus species richness (Ricklefs et al. 1999):

$$-\sum_{i=1}^{s}\left(\frac{ni}{N}\right) * LN\left(\frac{ni}{N}\right) \tag{2.4}$$

where:

ni is the number of individuals within the block, i.e. forest age, forest type, LN is the natural logarithm and *N* is the total number of observations within the block.

2.2.4.11 Forest Ownership

A forest ownership thematic map was obtained from Forest Service Research Data Archive (Hewes, 2014) as raster data, including three types of public ownership: federal, state, and local, as well as three types of private ownership: family, corporate private, and other private ownership which includes conservation and natural resource organizations, unincorporated partnerships and associations, and Native American tribal lands. For the objective of this study federal, state, and local forest ownership classes were re-coded into public forest, family and other private into non-corporate private forest (NCPF) and corporate private forest (CPF) (Figure 2.12).

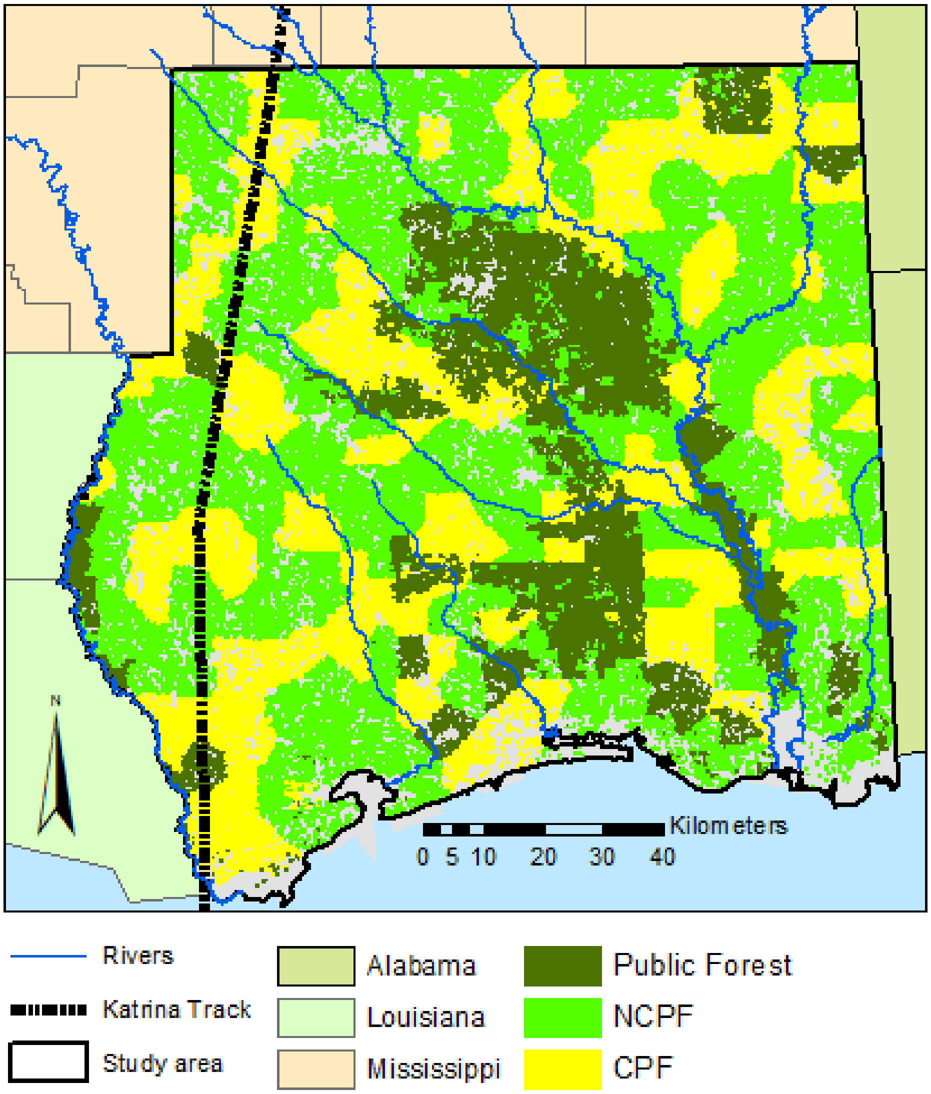


Figure 2.12 Distribution of forest ownership in study area Southeast Mississippi, USA.

Dark green = public forest, Green = non-corporate private forest (NCPF), Yellow = corporate private forest (CPF). Hurricane track was acquired from the Mississippi Automated Resource Information System; boundary and river locations were acquired from the United States Census Bureau; forest ownership was derived from Forest Service Research Data Archive.

About 22% of the forest land is under the ownership of public entities, 46% of the forestland in the study area was owned by non-corporate private, and approximately 32% of the forestland was under private corporate organizations (Figure 2.13).

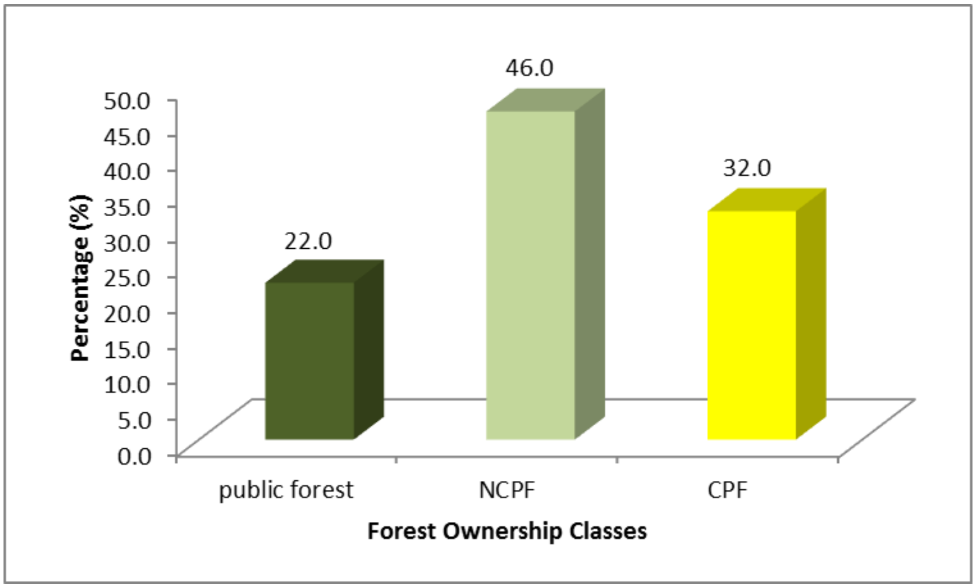


Figure 2.13 Proportion of forest ownership by type.

NCPF = non-corporate private forest, CPF = corporate private forest, and public forest. Forest ownership was derived from Forest Service Research Data Archive.

2.2.4.12 Rainfall

A dataset of rainfall was obtained from the National Weather Service as a point dataset. A raster rainfall map of 240 m x 240 m cell size was created using Inverse Distance Weighted (IDW) interpolation to estimate the rainfall values throughout the study area at unknown locations using the sampled values and distance to nearby known points (Bolstad 2008) (Figure 2.14). The weight allocated to each sampled point is an inverse extent of the separation to the unknown location that is being interpolated. This implies, the more faraway the point, the less weight the point has in evaluating the value at an un-sampled location.

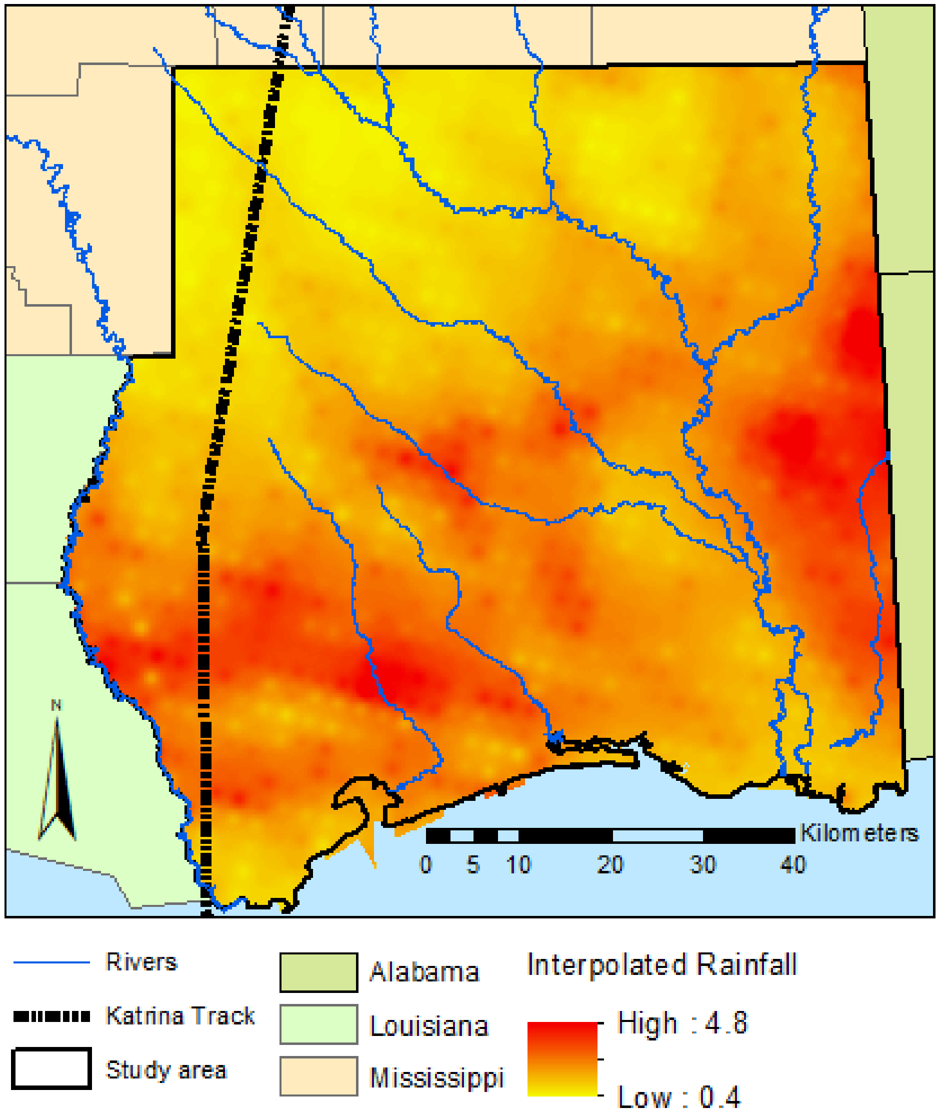


Figure 2.14 Inverse Distance Weighted interpolation map of rainfall within the study area in Southeast Mississippi

Hurricane track was acquired from the Mississippi Automated Resource Information System; boundary and river locations were acquired from the United States Census Bureau; Rainfall was derived from National Weather Service

2.3 Statistical Analysis

Two different statistic techniques (multiple and binary logistic regression) were used to examine the relationship between forest age diversity, forest type diversity, forest ownership, and rainfall as independent variables and NDVI percent change as the dependent variable. Initial multiple regression and binary logistic regression models were carried out on the entire study area. Additional multiple and binary logistic regressions (final models) were executed with the elimination of areas with high NDVI percent change within Pascagoula River basin because the high NDVI percent change was assumed mainly caused by defoliation. This area was believed to have high NDVI percent change not in the form of mechanical wind damage to the bole (shear and blowdown) but may be linked to defoliation. The Gulf Coast of Louisiana, Mississippi, and Alabama experienced wind, storm surge, and flooding damage during Hurricane Katrina and the surge penetrated at least 10 km inland in many portions of coastal Mississippi and up to 20 km inland along bays and rivers (Fritz et al. 2007, Stanturf et. al. 2007). The lower Pascagoula River Basin is dominated by hardwood species. Compared to upland forests, forests adjacent to streams and rivers showed a higher level of damage from hurricane (Wang and Xu 2009).

2.3.1 Multiple Regression

Multiple linear regression analysis was utilized to measure the amount of variation in the data and assess the relative importance of the independent variables (Ott and Longnecker, 2001). Previous studies examining the effects of several predictor variables on NDVI change such as (Oswalt and Oswalt 2008, and Doyle et al. 1995) have also used multiple linear regression. R^2 value was used to determine the strength of the relationship or the amount of variance described by the model and is confined to $0 < R^2 > 1$. Higher values of R^2 are desired and used to determine which linear model best fit the data (Xi et al. 2008).

Multiple linear regression was used to predict the potential severity of damage (NDVI percent change, Y_k). A multiple linear regression model was used to test the effect of forest age, forest types, and rainfall on NDVI percent change. The model for multiple linear regression, given n independent variables, is:

$$Y_k = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i3} + \beta_4 X_{i4} + e_k \tag{2.5}$$

for $i = 1,2,\ldots,n$.

where:

Y_k is the NDVI percent change (a proxy for possible wind damage) for observation k, a dependent variable to predict,

β_0 is the intercept, and

β_i is coefficient of the ith variable X_i.

e_k is a random variable such that, $e_{ij} \sim i.i.d.\,N(0, \sigma^2)$, iidn $(0,\sigma^2)$

The significance of parameters was tested at 5% significance level ($\alpha = 0.05$).

The independent variables (X_{in}) forest age diversity and forest type diversity indices were developed from 30 m Landsat-derived dataset. A rainfall value was interpolated by IDW technique. Table 2.1 provides a description of variables in the multiple linear regression model.

Table 2.1 Description of independent variables in the multiple linear regression

Variable name	**Description**
Forest age diversity index	Shannon-Weaver values from 0.08 to 1.76
Forest type diversity index	Shannon-Weaver values from 0.08 to 1.60
Rainfall	Interpolated amount of rainfall 0.4 to 4.8

2.3.2 Binary logistic regression

In this technique, the damage category/level was predicted based on the independent variables in the prediction model (Ott and Longnecker 2001). Oswalt and Oswalt (2008) and Wang and Xu (2009) reported the effects of several predictor variables on NDVI change and used binary logistic regression. The odds ratios (exponential values) were used to assess the influence of each predictor on the dependent variable. The logistic type model is preferred over the more conservative linear or non-linear models because it is designed to predict a binary response like presence or absence of NDVI change (Gumpertz and Pye 2000). A more technical advantage of logistic regression over ordinary regression has to do with the methods of estimation. Logistic regression incorporates information about the variance of binary/proportion data into the estimating equations to provide more efficient estimates than ordinary regression would.

Initially, NDVI percent change was expressed as a continuous variable. However, it was necessary to transform it into a binary variable for logistic regression. NDVI percent change was plotted as a frequency histogram which indicated some NBs in the distribution (Figure 2.6). The value of the natural break was 8.23 which was used to categorize the continuous distribution into a 0 and 1. In this case, zero represented values less than or equal to 8.23 whereas 1 denoted values greater than 8.23. Furthermore, three additional logistic models with threshold values namely 10, 15 and 20 were used to create binary NDVI percent change. The 10, 15 and 20 percent change thresholds were examined and created depending on the classes originally obtained from RTI. This means threshold values equal to and less than 10 were given a value of zero (assumed no damage) and values greater than 10 were given value of one (high NDVI percent change).

An initial logistic regression model was developed for the entire study area. Additional logistic regression (final model) was executed with the elimination of areas with high NDVI percent change in lower Pascagoula River area because high NDVI change was assumed mainly caused by defoliation. This area was believed to have high NDVI percent change not in the form of mechanical wind damage to the bole (shear and blowdown) but may be linked to defoliation.

The binary logistic regression technique was applied to determine the probability of forest areas having low or no damage (category 0) or high damage (category 1). Binary logistic regression is used to predict the probabilities of the different possible outcomes of a categorically distributed dependent variable, given a set of independent variables, which may be real, binary, categorical, or integer. The model is of the form:

$$Y = \log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + .. + \beta_n X_n + \varepsilon \tag{2.6}$$

where:

The dependent variable Y is the probability of low verses high damage,

β_n presents the log odds ratios,

X_n are the independent variables forest age diversity, forest type diversity, rainfall, and forest ownership, and

ε is the error term.

Table 2.2 provides a detailed description of variables in the binary logistic model.

Table 2.2 Description of independent variables in the binary logistic regression

Variable name	**Description**
Forest age diversity index	Shannon-Weaver values from 0.08 to 1.76
Forest type diversity index	Shannon-Weaver values from 0.08 to 1.60
Rainfall	Interpolated amount of rainfall 0.4 to 4.8
Forest ownership	1 if non-corporate private forest 0 otherwise 1 if corporate private forest 0 otherwise (public ownership is reference category)

The independent variables forest age diversity and forest type diversity were developed from 30 m Landsat-derived dataset. Rainfall was interpolated by IDW technique. Forest ownership was the aforementioned three ownership classes.

The study hypotheses examined in this analysis were as follows: It is expected that as the forest age diversity increases, NDVI percent change decreases. As forest type diversity and rainfall increases, NDVI percent change increases. Non-corporate private forest ownership class is likely to be more vulnerable to wind damage than corporate and publicly owned forests. The significance of parameters was determined at 5% significance level ($\alpha = 0.05$).

CHAPTER III

RESULTS AND DISCUSSION

This chapter is organized into several sub-sections. First, multiple regression model outcomes are examined which indicate the impact of forest age diversity and forest type diversity on NDVI percent change. Forest age and forest type were transformed into Shannon-Weaver diversity indexes which are essentially continuous in nature. Second, binary logistic indices were used to examine the association between NDVI percent change and forest age diversity as well as NDVI percent change and forest type diversity.

3.1 Multiple regression results

An initial multiple regression model was developed for the entire study area. Additional multiple regression (final model) was executed after elimination of areas with high NDVI percent change in Pascagoula River area because the area was a considerable distance from the hurricane track and high NDVI change was assumed mainly caused by defoliation (Table 3.1). This area was believed to have high NDVI percent change not in the form of mechanical wind damage to the bole (shear and blowdown) but maybe linked to defoliation. The lower Pascagoula River Basin is dominated by hardwood species. Kupfer et al. (2008) found hardwood vegetation located in bottomlands and along river channels most susceptible to damage.

Outputs from initial and final multiple regression models revealed that all predictors were statistically significant ($p<0.05$). For the study area in general, increases in the forest type Shannon-Weaver Index diversity and rainfall were associated with increases in percent NDVI change statistics for the full spatial extent (initial model) and the restricted spatial extent (lower Pascagoula River Basin removed; final model) (Table 3.1).

Table 3.1 Comparison of multiple regression results of initial and final models to predict NDVI change for Southeast Mississippi.

Variable	**Multiple Regression Initial Model**		**Multiple Regression Final Model**	
	Beta	S.E.***	Beta	S.E.***
Constant	7.837	0.047	7.015	0.043
Age diversity	-1.225*	0.049	-0.861*	0.045
Type diversity	0.809*	0.047	1.165*	0.044
Rainfall	0.809*	0.022	0.759*	0.020

Change data derived from Radiance Technologies Institute; Forest age was derived from Mississippi Institute of Forest Inventory; Forest type was derived from Mississippi Institute of Forest Inventory. * = statistically significant. *** = standard error.

As forest age diversity changed by one unit, NDVI percent change for initial and final models decreased by 1.225 and 0.861units respectively, holding other factors constant. In both models, a one unit change in forest type diversity was associated with an increment in NDVI percent change of 0.809 and 1.165 units respectively, holding other factors constant. Likewise, as rainfall increases in both models by one unit, NDVI percent change increased by 0.809 and 0.759 units respectively, holding other factors constant.

Table 3.2 shows multiple regression results with NDVI percent change for each of the five zones for the full spatial extent and before removal of Pascagoula River area. Outputs from Zone 1 revealed that all predictor variables were statistically significant

($p<0.05$). As forest age diversity changed by one unit, NDVI percent change decreased by 1.127 units, holding other factors constant. On the other hand, an increase in forest type diversity led to an increment in NDVI percent change by 1.235 units, holding other factors constant. Rainfall had a negative impact on NDVI percent change in Zone 1, which is contrary to expectation.

Table 3.2 Multiple regression results obtained from study area for each zone before eliminating high normalized difference vegetation index (NDVI) change in lower Pascagoula River Basin in Mississippi.

Variable	**Zone 1**		**Zone 2**		**Zone 3**		**Zone 4**		**Zone 5**	
	Beta	S.E.***	Beta	S.E.***	Beta	S.E.***	Beta	S.E.***	Beta	S.E.***
Constant	11.880	0.184	6.874	0.091	6.938	0.088	9.067	0.114	6.018	0.100
Age diversity	-1.127*	0.161	-0.347*	0.096	-0.730*	0.088	-2.195*	0.102	-1.12*	0.110
Type diversity	1.235*	0.159	0.082	0.092	1.034*	0.084	-0.461*	0.102	1.690*	0.111
Rainfall	-0.613*	0.074	1.570*	0.043	0.046*	0.046	0.871*	0.059	0.459*	0.024

Change data derived from Radiance Technologies Institute; Forest age was derived from Mississippi Institute of Forest Inventory; Forest type was derived from Mississippi Institute of Forest Inventory. * = statistically significant. *** = standard error.

In Zone 2, forest type diversity was statistically insignificant on changes in NDVI ($p>0.05$), however, the remaining set of predictors had a significant effect on NDVI percent change. The marginal increments in forest age diversity coefficient led to a decrease in NDVI percent change by 0.347 units, holding other factors constant. On the other hand, as rainfall increased by one unit, NDVI percent change increased by 1.570 units, holding other factors constant.

In Zone 3, all predictor variables were statistically significant at ($p<0.05$). A marginal increase in forest age diversity coefficients led to a 0.730 unit decrease in the NDVI percent change. However, forest type diversity and rainfall were associated with an increase in NDVI percent change by 1.034 and 0.046 respectively, holding other factors constant.

In Zone 4, all predictor variables were statistically significant at ($p<0.05$). The increase of forest age diversity coefficients led to a decrease in NDVI percent change by 2.195 units, holding other factors constant. Similarly, the increase of forest type diversity coefficients led to a decrease in NDVI percent change by 0.461 units holding other factors constant. The outcome for forest type diversity is inconsistent with the hypothetical assumption. However, as rainfall increased, NDVI percent change also increased by 0.871, holding other factors constant.

Multiple regression results for Zone 5 showed that all independent variables were statistically significant ($p<0.05$). Again, as forest type diversity and rainfall coefficients increased, NDVI percent change also increased by 1.690 and 0.459 respectively, holding other factors constant. In all zones, Shannon-Weaver Index scale of the forest age diversity indicated that the increase in forest age diversity led to decrease in NDVI percent change. While all regression models were statistically significant as reflected by the F-test, the R-square values were low.

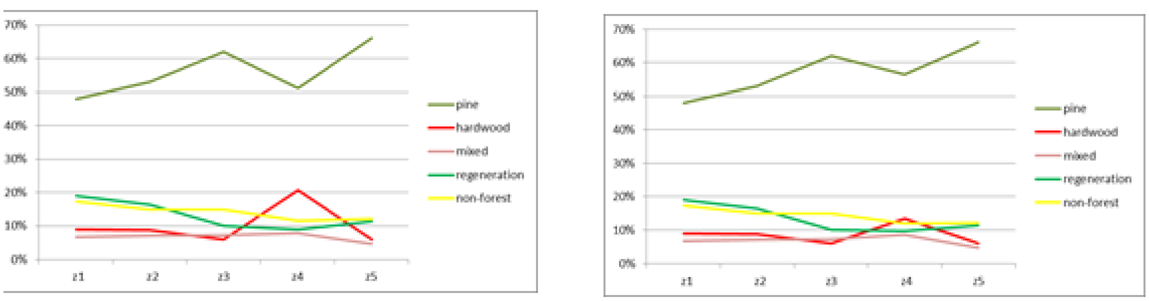
Table 3.3 indicates multiple regression results of the data after eliminating the Pascagoula River area. It was assumed that there was little mechanical wind damage to the bole (shear and blowdown) and NDVI percent change was mainly linked to defoliation (explained earlier).

Table 3.3 Multiple regression results obtained from study area for each zone after the eliminating high normalized difference vegetation index (NDVI) change in the lower Pascagoula River Basin.

Variable	**Zone 1**		**Zone 2**		**Zone 3**		**Zone 4**		**Zone 5**	
	Beta	S.E.***	Beta	S.E.***	Beta	S.E.***	Beta	S.E.***	Beta	S.E.***
Constant	11.880	0.184	7.014	0.087	7.408	0.084	6.444	0.082	5.483	0.092
Age diversity	-1.127*	0.161	-0.390*	0.093	-0.630*	0.084	-1.193*	0.075	-0.92*	0.101
Type diversity	1.235*	0.159	0.139	0.089	0.866*	0.081	1.106*	0.074	1.447*	0.102
Rainfall	-0.613*	0.074	1.347*	0.041	0.503*	0.044	0.720*	0.041	0.586*	0.038

Change data derived from Radiance Technologies Institute; Forest age was derived from Mississippi Institute of Forest Inventory; Forest type was derived from Mississippi Institute of Forest Inventory. * = statistically significant. *** = standard error.

Outputs from the final model revealed that all predictors were statistically significant ($p<0.05$), except for forest type diversity in Zone 2. Since the same area were used in the initial and final models in all zones except in Zone 4, the results and trends of the final model were not much different from the initial model (before excluding Pascagoula River area). In general, models summarized in Table 3.2 show a similar trend with models given in Table 3.3 except in Zone 4 (where most of Pascagoula River is located) where the forest type diversity coefficient changed from negative to positive also there was big drop in hardwood cover. Figure 3.1 illustrates the change in percentage of forest type classes before and after elimination of the lower Pascagoula River area, which led to significant decrease in hardwoods type.



(a) (b)

Figure 3.1 Change in percentage of forest type classes before and after elimination of the lower Pascagoula River area.

(a) Forest type classes percent area cover within each zone before elimination of lower Pascagoula River Basin (b) Forest type classes percent area cover within each zone after elimination of lower Pascagoula River Basin.

The difference in the coefficient magnitude in Table 3.3 is attributed to the removal of area associated with the lower Pascagoula River which had a high NDVI percent change. Hence, the increase of forest type diversity coefficient in Zone 4 was associated with an increase in NDVI percent change by 1.106 units holding other factors constant.

3.2 Binary logistic regression results

Binary Logistic Regression was considered in order to include the categorical variable forest ownership. Logistic regression was used because the object of this research was to test the relationship between the binary independent variable (forest ownership) as well as the continuous variables (forest age diversity, forest type diversity, and rainfall) and the dependent variable (NDVI percent change).

The binary logistic regression in Tables 3.4, 3.5, 3.6, 3.7, 3.8 and 3.9 show Beta values, p-values, and the odds ratios for the full spatial extent (initial logistic model) and the restricted spatial extent (Pascagoula River removed) (final logistic model). This lower Pascagoula River Basin was believed to have high NDVI percent change not as mechanical wind damage to boles (shear and blowdown) but was assumed due to defoliation (explained in section 2.3). The results of the NB analysis versus the 10, 15 and 20 percent cutoff levels of NDVI percent change are shown for the entire study area model and also the five zones.

In Table 3.4 the initial binary logistic regression model development outputs are presented on the entire study area and the result gave a low R-square and inconsistencies with the predictor trends in the models. Therefore, another final logistic regression model was executed with the elimination of area with high NDVI percent change in Pascagoula River area (Final Model outputs in Table 3.4).

Table 3.4 Comparison of binary logistic regression results of the full spatial extent (initial model) and the restricted spatial extent (final model) after lower Pascagoula River Basin was removed.

Variable	**Logistic Regression Initial Model**			**Logistic Regression Final Model**		
	Beta	S.E.***	Exp**	Beta	S.E.***	Exp**
Public Forest	-0.007	0.015	0.993	0.129	0.014	1.137*
CPF	0.053	0.013	1.054*	0.045	0.013	1.046*
Age diversity	-0.288	0.019	0.750*	-0.336	0.018	0.714*
Type diversity	0.423	0.018	1.526*	0.366	0.018	1.442*
Rainfall	0.332	0.008	1.394*	0.342	0.008	1.407*
Constant	-0.826	0.019	0.438	-0.713	0.019	0.490

Change data derived from Radiance Technologies Institute; Forest age was derived from Mississippi Institute of Forest Inventory; Forest type was derived from Mississippi Institute of Forest Inventory. * = statistically significant. **Exp = odds ratio. *** = standard error.

Outputs from the full spatial extent (initial logistic model) and the restricted spatial extent after the elimination of Pascagoula River removed (final logistic model) revealed that all predictor variables were significant except for public forest in the initial model ($p<0.05$). When compared with the reference category non-corporate private forest (NCPF), corporate private forest (CPF) for initial and final models had odds ratios (Exp, odds ratios in Table 3.4) of 1.054 and 1.046 respectively of experiencing a high NDVI percent change, holding other factors constant. As forest age diversity changed by one unit, the probability of a high NDVI percent change for initial and final models decreased by 0.750 and 0.714 units respectively, holding other factors constant. However, in the full spatial extent (initial model) and the restricted spatial extent (Pascagoula River removed) model the increase of forest type diversity was associated with 1.526 and 1.442 increment in odds ratio of high NDVI percent change respectively, holding other factors constant. Likewise as rainfall increases in both models by one unit the odds ratio of high NDVI percent change increases by 1.394 and 1.407 units respectively, holding other factors constant. In general, there is no significant difference between both models except magnitude of values of the odds ratio, which is due to the removal of the Pascagoula River area in the final model.

Table 3.5 shows the logistic regression results by zone (Figure 2.4) based on NDVI percent change using the NB classification (Figure 2.6). In Zone 1, CPF, forest age diversity, and forest type diversity were statistically significant whereas public forest and rainfall were statistically insignificant ($p>0.05$). Comparing the reference category NCPF with CPF, an odds ratio of 0.832 units on the NDVI percent change was obtained while holding other factors constant. However, a marginal change in forest age diversity coefficient was associated with 0.767 unit decrease in the odds of experiencing a high NDVI percent change, holding other factors constant. Conversely, the forest type diversity coefficient was associated with a 1.209 unit increase in the odds of NDVI percent change, holding other factors constant.

Table 3.5 Binary logistic regression results (natural break, NB, model) obtained from study area for each zone before eliminating high normalized difference vegetation index (NDVI) change in the lower Pascagoula River Basin.

Variable	Zone 1			Zone 2			Zone 3			Zone 4			Zone 5		
	Beta	S.E.***	Exp**	Beta	S.E.***	Exp**	Beta	S.E.***	Exp**	Beta	S.E.***	Exp**	Beta	S.E.***	Exp**
Public Forest	0.021	0.072	1.021	0.386	0.034	1.471*	-0.220	0.026	0.802*	0.302	0.028	1.353*	-0.598	0.073	0.550*
CPF	-0.183	0.030	0.832*	0.020	0.024	1.020	-0.044	0.033	0.957	-0.029	0.028	0.971	0.299	0.033	1.348*
Age diversity	-0.265	0.053	0.767*	-0.009	0.040	0.991	-0.253	0.037	0.776*	-0.627	0.036	0.534*	-0.440	0.053	0.644*
Type diversity	0.190	0.052	1.209*	-0.049	0.038	0.952	0.358	0.036	1.430*	0.299	0.036	1.348*	0.709	0.053	2.033*
Rainfall	0.012	0.025	1.012	0.577	0.018	1.781*	0.465	0.020	1.592*	0.356	0.021	1.427*	0.242	0.019	1.273*
Constant	0.526	0.066	1.692	-0.828	0.039	0.437	-0.771	0.038	0.463	-0.647	0.043	0.524	-1.446	0.052	0.235

Change data derived from Radiance Technologies Institute; Forest age was derived from Mississippi Institute of Forest Inventory; Forest type was derived from Missisippi Institute of Forest Inventory. * = statistically significant. **Exp = odds ratio. *** = standard error.

In Zone 2, only public forest and rainfall were statistically significant ($p<0.05$). When compared with the reference category, publicly owned forest had an odds ratio of 1.471 units of experiencing a high NDVI percent change, holding other factors constant. As rainfall increases by one unit, the odds ratio of high NDVI percent change increases by 1.781 units, holding other factors constant. CPF, forest age diversity and forest type diversity were not statistically significant in this model ($p>0.05$).

In Zone 3, all variables were statistically significant ($p<0.05$) except for CPF. When compared with the reference category, publicly owned forest had an odds ratio of 0.802 units of experiencing a high NDVI percent change, holding other factors constant. Forest age diversity had an odds ratio of 0.776 implying that as forest age diversity increases by one unit, the probability of high NDVI percent change decreases by 0.224. Forest type diversity and the rainfall increased the odds of high NDVI percent change by factors of 1.430 and 1.592 respectively.

In Zone 4, when compared with the reference category NCPF, public forest had an odds ratio of 1.353 of experiencing a high NDVI percent change, holding other factors constant. In addition, forest type diversity and rainfall each increased the odds of a high NDVI percent change by factors of 1.348 and 1.427 respectively. Nevertheless, the forest age diversity had an odds ratio of 0.534 of experiencing a high NDVI percent change, holding other factors constant. There was no statistical association between CPF ownership and NDVI percent change ($p>0.05$).

Regarding Zone 5, all predictor variables had a statistically significant influence on the probability of high NDVI percent change ($p<0.05$). Public forests had a probability of 0.550 of experiencing a high NDVI percent change compared to the baseline category of NCPF. However, when compared with the reference category, CPF had an odds ratio of 1.348 of experiencing a high NDVI percent change, holding other factors constant. Again, as in zones 1 to 4, forest age diversity in Zone 5 had a negative sign with an odds ratio of 0.644 implying that more diverse forest was associated with a low NDVI percent change. With odds ratios of 2.033 and 1.273 respectively, forest type diversity and rainfall had the effect of increasing high NDVI percent change.

Table 3.6 indicates binary logistic regression results of the data subsequent to the elimination of Pascagoula River area (which is mainly located in Zone 4). The results and trends of the final model were similar to the initial model before excluding Pascagoula River area. In general, results in Table 3.6 showed a similar trend with results in Table 3.5 except in Zone 4 where the public forest coefficient changed from positive to negative. Because of the elimination of Pascagoula River area which is dominated by public ownership, the overall ratio of public forest to NCPF in this zone dropped dramatically hence the change of sign. In general, there was a slight difference between both models in terms of the magnitude which is due to the different excluding of Pascagoula River area.

Table 3.6 Binary logistic regression results (natural break, NB, model) obtained from study area for each zone after eliminating high normalized difference vegetation index (NDVI) change in the lower Pascagoula River Basin.

Variable	**Zone 1**			**Zone 2**			**Zone 3**			**Zone 4**			**Zone 5**		
	Beta	S.E.***	Exp**	Beta	S.E.***	Exp**	Beta	S.E.***	Exp**	Beta	S.E.***	Exp**	Beta	S.E.***	Exp**
Public Forest	0.021	0.027	1.021*	0.371	0.035	1.449*	-0.190	0.027	0.827*	-0.094	0.032	0.911*	-0.663	-0.077	0.516*
CPF	-0.183	0.030	0.832*	0.021	0.025	1.021	-0.054	0.034	0.948	0.028	0.029	1.028	0.264	0.034	1.302*
Age diversity	-0.265	0.053	0.767*	-0.16	0.040	0.984	-0.239	0.038	0.787*	-0.534	0.039	0.586*	-0.406	0.054	0.667*
Type diversity	0.190	0.052	1.209*	-0.039	0.038	0.961	0.341	0.037	1.406*	0.598	0.039	1.818*	0.681	0.054	1.975*
Rainfall	0.012	0.025	1.012*	0.535	0.018	1.707*	0.355	0.021	1.427*	0.382	0.022	1.465*	0.277	0.020	1.319*
Constant	0.526	0.066	1.692	-0.798	0.039	0.450	-0.685	0.039	0.504	-1.106	0.046	0.331	-1.581	0.053	0.206

Change data derived from Radiance Technologies Institute; Forest age was derived from Mississippi Institute of Forest Inventory; Forest type was derived from Mississippi Institute of Forest Inventory. * = statistically significant. **Exp = odds ratio. *** = standard error.

Tables 3.7, 3.8, and 3.9 represent the results obtained from different NDVI threshold levels (10, 15 and 20). From threshold 10 table (3.7), the regression coefficients are only slightly different from the NB results. This is because the NB threshold (8.23) is very close to the NDVI threshold 10. However, for the threshold 15 and 20 tables (3.8 and 3.9), the difference in the regression coefficients are noticeable compared to the NB results due to the difference between both thresholds and the NB. For example, the odds ratios for CPF in Zone 1, NB, 15 and 20 were 0.832, 0.584, and 0.442 respectively. The odds ratio for public forest in Zone 3 for NB, 15 and 20 were 0.827, 0.442, and 0.359 respectively. On the other hand, odds ratios for forest age diversity in Zone 4 for NB, 15 and 20 were 0.586, 0.549, and 0.621 respectively.

Table 3.7 Binary logistic regression results obtained from study area for each zone at a normalized difference vegetation index (NDVI) threshold of 10 after eliminating high NDVI change in the lower Pascagoula River Basin.

Variable	**Zone 1**			**Zone 2**			**Zone 3**			**Zone 4**			**Zone 5**		
	Beta	S.E.***	Exp**	Beta	S.E.***	Exp**	Beta	S.E.***	Exp**	Beta	S.E.***	Exp**	Beta	S.E.***	Exp**
Public Forest	-0.029	0.073	0.972	0.384	0.036	1.468*	-0.133	0.027	0.875*	-0.027	0.031	0.973	-0.556	0.071	0.574*
CPF	-0.161	0.031	0.851*	0.030	0.025	1.030	-0.011	0.033	0.989	0.051	0.029	1.052	0.261	0.033	1.299*
Age diversity	-0.274	0.053	0.760*	0.055	0.040	1.057	-0.250	0.037	0.779*	-0.569	0.039	0.566*	-0.472	0.052	0.624*
Type diversity	0.114	0.052	1.121*	-0.207	0.038	0.813*	0.211	0.036	1.235*	0.525	0.038	1.690*	0.582	0.052	1.790*
Rainfall	0.007	0.025	1.008*	0.524	0.019	1.689*	0.317	0.021	1.373*	0.366	0.21	1.442*	0.272	0.019	1.312*
Constant	0.680	0.066	1.974	-0.576	0.039	0.562	-0.415	0.038	0.660	-0.856	0.045	0.425	-1.339	0.051	0.262

Change data derived from Radiance Technologies Institute; Forest age was derived from Mississippi Institute of Forest Inventory; Forest type was derived from Mississippi Institute of Forest Inventory. * = statistically significant. **Exp = odds ratio. *** = standard error.

Table 3.8 Binary logistic regression results obtained from study area for each zone at a normalized difference vegetation index (NDVI) threshold of 15 after eliminating high NDVI change in the lower Pascagoula River Basin.

Variable	Zone 1			Zone 2			Zone 3			Zone 4			Zone 5		
	Beta	S.E.***	Exp**	Beta	S.E.***	Exp**	Beta	S.E.***	Exp**	Beta	S.E.***	Exp**	Beta	S.E.***	Exp**
Public Forest	-0.052	0.088	0.950	0.273	0.054	1.313*	-0.817	0.059	0.442*	-0.400	0.089	0.670*	-0.513	0.175	0.598*
CPF	-0.538	0.040	0.584*	0.193	0.042	1.213*	-0.320	0.067	0.726*	-0.094	0.076	0.910	0.158	0.074	1.171*
Age diversity	-0.501	0.070	0.606*	-0.514	0.068	0.598*	-0.390	0.080	0.677*	-0.600	0.104	0.549*	-0.282	0.120	0.754*
Type diversity	0.677	0.069	1.968*	0.536	0.065	1.709*	0.626	0.077	1.871*	0.713	0.102	2.040*	0.650	0.118	1.916*
Rainfall	-0.297	0.032	0.743*	0.446	0.029	1.562*	0.040	0.041	1.040	0.067	0.055	1.070	0.004	0.044	1.004
Constant	-0.722	0.083	0.486	-3.102	0.067	0.045	-2.551	0.077	0.078	-3.368	0.120	0.034	-3.287	0.117	0.037

Change data derived from Radiance Technologies Institute; Forest age was derived from Mississippi Institute of Forest Inventory; Forest type was derived from Mississippi Institute of Forest Inventory. * = statistically significant. **Exp = odds ratio. *** = standard error.

Table 3.9 Binary logistic regression results obtained from study area for each zone at a normalized difference vegetation index (NDVI) threshold of 20 after eliminating high NDVI change in the lower Pascagoula River Basin.

Variable	**Zone 1**			**Zone 2**			**Zone 3**			**Zone 4**			**Zone 5**		
	Beta	S.E.***	Exp**	Beta	S.E.***	Exp**	Beta	S.E.***	Exp**	Beta	S.E.***	Exp**	Beta	S.E.***	Exp**
Public Forest	0.164	0.0117	1.78	-0.052	0.106	0940	-1.024	0.108	0.359*	-0.428	0.170	0.652*	-0.990	0.369	0.372*
CPF	-0.817	0.061	0.442*	0.296	0.073	1.345*	-0.673	0.128	0.510*	-0.147	0.144	0.863	0.189	0.132	1.208
Age diversity	-0.550	0.103	0.577*	-0.466	0.122	0.628*	-0.431	0.140	0.650*	-0.477	0.197	0.621*	-0.107	0.216	0.898
Type diversity	0.745	0.103	2.106*	0.640	0.116	1.896*	0.593	0.135	1.810*	0.619	0.192	1.857*	0.494	0.214	1.639*
Rainfall	-0.735	0.049	0.480*	0.393	0.051	1.481*	-0.085	0.072	0.919	0.067	0.104	1.069	-0.233	0.084	0.792*
Constant	-0.748	0.120	0.473	-4.401	0.120	0.021	-3.446	0.129	0.032	-4.688	0.226	0.009	-4.089	0.212	0.017

Change data derived from Radiance Technologies Institute; Forest age was derived from Mississippi Institute of Forest Inventory; Forest type was derived from Mississippi Institute of Forest Inventory. * = statistically significant. **Exp = odds ratio. *** = standard error.

3.3 Discussion

Multiple linear regression and binary logistic regression models were used to examine the relationship of forest age diversity, forest type diversity, rainfall and forest ownership variables to NDVI percent change that represented assumed wind-related damage in the study area. The analysis in the multiple regression and binary logistic regression techniques showed the variables were statistically significant although there were variations from zone to zone. The mapped damage zones numbered in ascending order from 1 through 5 (Figure 2.4), with Zone 1 encompassing landfall (containing the greatest amount of forecast damage) and Zone 5 furthest from landfall (containing the least amount of forecast damage). Except in Zone 4 in the initial and final models, the regression coefficients of the variables were almost the same. Therefore, elimination of Pascagoula river area (predominantly broadleaf deciduous trees) did not result in substantial changes in parameter estimates except in Zone 4.

The findings of this study indicate that as forest age diversity decreases, wind related damage increases, which follows the original expectations. This was observed for the entire study area (initial and final models) as well as zonal levels. The high difference in forest vertical structure has an influence on areas being shaded by large tree crowns in the upper canopy. The nature of the vegetation that occur pre-hurricane in coastal forest communities, particularly forests that have large trees with lots of shadow, have low NDVI cell values in pre-storm products. "Shaded areas return a near zero reflectance value which result in a lower overall average reflectance for the pixel" (Wilkinson 2011). On the other hand, high NDVI values in post-storm products were observed, this might be due to the reduction of shadow effect as well as the exposure of small dense evergreen vegetation in the midstory and understory. Furthermore, as forest age becomes more diverse, the vertical structure of the forest canopy becomes uneven, the high difference in forest vertical structure may result in areas of midstory and understory being protected by tree crowns from direct damage (Imbert et al. 1996). Hence, protected vegetation in midstory and understory was exposed to less damage which resulted in low NDVI percent change. Potential for damage increases as forest age becomes more homogenous. This result contradicts the findings of Garrigues (2011) who observed that the probability of damage decreased with tree height variation, which is a proxy for forest age diversity. In order to reduce vulnerability to damage from future hurricanes, forest management objectives must be examined such as incorporating more complex stand structures (diverse age groups) into ongoing forest management. The hypothetical proposition between forest age diversity and wind damage was therefore accepted ($P<0.05$).

Forest type diversity indicated a direct relationship with NDVI percent change; as forest type diversity increases the NDVI percent change increases. The increase in forest type diversity showed a positive relationship with NDVI percent change in all models except in Zone 4. The high concentration of NDVI percent change in lower Pascagoula River Basin located in Zone 4 resulted in a negative relationship to forest type diversity. The positive relationship between forest type diversity and NDVI percent change might be explained by the influence of the varying types of land covers that compose the forest type diversity. Forest type diversity is defined by the mixture of open land (non-forest), pine forest, hardwoods, mixed and regeneration land-cover classes. The high divergent structure between non-forest and regeneration and other forest type classes caused an increase in the edge density, therefore, open land surrounding forest fragments provide less resistance to winds allowing wind to move across the cleared landscape which makes forestland more susceptible to damage (Peltola et al. 1999, Laurance, and Curran 2008). Areas encompassing different forest types (diverse forest) are associated with high concentration of edges. This assertion is supported by Harper et al. (2005) who suggested that windy conditions are associated with increased tree damage particularly on forest edges. He also stated that greater patch contrast (higher forest type diversity) is associated with greater edge influence.

Multiple and binary logistic regression analysis examining NDVI percent change for the study area identified a significant relationship between NDVI percent change and rainfall. These results indicate that more rainfall accounted for more NDVI percent change and the result shows that the rainfall variable had a positive correlation with the NDVI change in all models except in Zone 1. The negative results in Zone 1 negates the expectation that more rainfall might have resulted in more damage due to the nature of heavy rainfall associated with soil saturation which affects the root-soil holding (Kupfer et al. 2008). This exception might be due to the nature of data in this zone (greater variability) affected by the variation of distance and position from the storm eye, wind speed, direction, duration of gusts, and the cyclic nature of the hurricane that could have resulted in heavy rainfall in a given patch and low rainfall in other patches. This can be partly explained by the nature of the combination of inner and feeder bands in the hurricane (Guinn and Schubert 1993). Graumann (2005) stated that as the heavy rain and thunderstorms transfer momentum from the level of highest winds (above the surface) down closer to the surface, the heaviest bands of rainfall shown on radar coincide with the strongest wind gusts at the surface. The relationship between NDVI percent change and rainfall for Zones 2 through 5 (Figure 2.4) showed a positive trend implying that more rainfall led to a higher NDVI percent change. This result is corroborated by Foster (1988) in central New England and Kupfer et al. (2008) who argued that catastrophic hurricane wind damage on vegetation may be explained by the very high levels of precipitation that accompanied the storm, saturating the soil and loosening the roots resulting in high uprooting damage.

According to the binary logistic regression model, the results from the entire study area showed public forest and CPF were at greater risk of forest damage compared to baseline category of NCPF on a landscape level. This result contradicts the expected hypothesis. This might be due to the coarse nature of ownership data used. The NCPF category comprises small to very big tracts. Large NCPF tracts have same character as more contiguous public and CPF forests which confuses NCPF with the other forest ownership types. The coarse spatial resolution of ownership data hindered the differentiation between fragmented and non-fragmented forest. Moreover, these observed results might be due to silviculture practices related to reducing risk of wind damage on public forests. Stanturf et al. (2007) argued that forest management practices on public land must reflect the existing regulations. As such, this partially limits the possibility of implementing appropriate silvicultural practices on large areas like heavy thinning and convert stands type to the more resilient species to reduce risk of hurricane damage. After the elimination of lower Pascagoula River area, results from the zone model showed that public forests in zones 3, 4, and 5 and CPF in Zone 1 had a lesser risk of forest damage compared to NCPF. This change is due to the improved consistency of data within each zone when compared to the entire study area data with reducing variability by removing the lower Pascagoula River area. In general, public forest, CPF and larger NCPF are more active forest managers than owners of smaller parcels. Larger forest tracts also tend to be less fragmented by non-forest development and can therefore be better managed for forest habitat. Therefore, maintaining forest ownerships in larger tracts can improve efficiency and effectiveness of conservation and reducing the susceptibility to wind damage.

3.4 Conclusion

The use of remote sensing and GIS techniques provided an approach to examine the severity of wind damage created by Hurricane Katrina in southeast Mississippi to determine how the disturbance was influenced by fragmentation based on forest age diversity, forest type diversity and forest ownership.

NDVI percent change (assumed wind related damage) following Hurricane Katrina over a large, diverse landscape was most strongly related to forest age diversity and forest type diversity as well as rainfall. Forest age diversity showed a negative association with the NDVI percent changes while forest type diversity and rainfall indicated a positive relationship. Forest managers and owners can reduce natural disturbance induced damage by managing their forests in more heterogeneous age groups across landscapes which will decrease the possibility of wind damage.

There was no consistent relationship between NDVI percent change and forest ownership variable. However, that does not mean that this variable is not important. Management practices are seemingly masked by forest age and forest type variables which are associated with forest ownership. Forest management practices related to tree species, tree age, stand density, and edge area ratio are controlled by landowner’s goals.

It must be mentioned that previous studies mostly used forest age as a parameter to assess impact on aspects such as tree mortality, succession or forest productivity. For example, Rich et al. 2007 used stand age to determine the wind-throw mortality in forests. Also, previous studies compared different sorts of wind damage and difference effects of damage on the physical structures of coniferous and hardwoods (Boucher et al.1990, Foster 1988). Nonetheless, in this research forest age diversity and forest type diversity were used, because these variables were created differently (for example age versus age diversity in this study) and, therefore, it was difficult to compare this research outputs with previous work (such as Rich et al. 2007). In order to more fully understand the effects on vulnerability of fragmentation, management systems, and forest structure additional research is needed. In future research, coupling high resolution remote sensing products such as Landsat with LiDAR data would better explain the relationship between severity of damage and forest age, forest type, ownership since the amount of information relative to the structure of a forest will increase greatly with use of LiDAR data.

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