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Spatial Analysis of Landscape Dynamics to Meteorological Changes in the Gulf of Mexico Coastal Region

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By

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The forest ecosystem is a dominant landscape in the Gulf of Mexico (GOM) coastal region. Currently, many studies have been carried out to identify factors that drive forest dynamics. Changes in meteorological conditions have been considered as the main factors affecting the forest dynamics. For this study, the statistical regression analysis was used for modeling forest dynamics. Meteorological impact analysis was driven by observed data from PRISM (parameter-elevation regressions on independent slopes model) climate dataset. The forest dynamics was characterized by an indicator, the normalized difference vegetation index (NDVI). The objectives of this study are to 1) to specify and estimate statistical regression models that account for forest dynamics in the Golf of Mexico coastal region, 2) to assess which model used to capture the relationship between forest dynamics and its explanatory variables with the best explanatory power, and 3) to use the best fitted regression model to explain forest dynamics. By using fixed-effects regression methods: ordinary least squares (OLS) and geographically weighted regression (GWR), the sample-point-based regression analysis showed that meteorological factors could generally explain more than half of variation in forest

dynamics. In respect of the unexplained variation of forest dynamics, the necessity of using soil to explain forest dynamics was then discussed. The result suggested that the forest dynamics could be explained by both meteorological parameters and soil texture. One of the basic considerations in this study is to include the spatiotemporal heterogeneity caused by seasonality and forest types. The model explanatory power was found differ among forest types (spatially) and seasons (temporally). By constructing regression models with randomly varying intercepts and varying slopes, the linear mixed-effects model (LMM) was fitted on composite county-based data (e.g., precipitation, temperature and NDVI). The use of LMMs was proved to be appropriate for describing forest dynamics to mixed-effects induced by meteorological changes. Based on this finding, I concluded that meteorological changes could play a significant role in forest dynamics through both fixed-effects and random-effects.

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CHAPTER I

INTRODUCTION

The forest dynamics was observed and interpreted in many ways. Crookston et al (2010) treated it as changes in forest stand (e.g., changes of tree volume and species distributions, and growth and mortality rates). Pretzsch (2009) used forest dynamics to indicate changes in forest structure and composition, including forest response to anthropogenic and natural disturbances. Some studies on forest dynamics were concerned with gap (i.e., small openings formed in the forest canopy that are then filled with other trees) dynamics of forests, which refers to the gap formation and closure (Yamamoto 2000; Bossel and Krieger. 1991). Moreover, some studies placed focus on forest dynamics from a carbon modeling perspective by quantifying the biomass consequences of forest disturbance and regrowth processes, which was known as forest biomass dynamics (Powell et al. 2010; Nascimento and Laurance. 2004; Hughes et al. 1999). Seasonal variations of NDVI (Normalized Difference Vegetation Index) are always used as a proxy for the forest dynamics (Soudani et al. 2012; Beck et al. 2006)

Satellite remote sensing could play an important and effective role obtaining information of forest dynamics (Giri et al. 2007). Remote sensing based vegetation index such as the NDVI could be utilized as the indicator of forest dynamics. NDVI is always calculated from low-correlated, red and near infrared bands, which is one of the most common measures of vegetation information. It is highly correlated to biophysical parameters such as vegetation biomass and the fraction of green vegetation cover (Goward et al. 1985; Sellers 1987; Myneni et al. 1995; Birky 2001; Boelman et al. 2003; Verbesselt et al. 2010; Zhao et al. 2011; Li and Fox 2012). It is also closely related to annual cycles of vegetation and forest phenology (e.g., green-up, peak and offset of development) (McCloy and Lucht 2004). The surface area of the NDVI implies the area of trees for both site and area (Meng et al. 2007). The MODIS (Moderate Resolution Imaging Spectroradiometer) NDVI product has been widely used to indicate forest dynamics (Otto et al., 2014; Li et al., 2013; Zhao et al., 2011; Verbesselt et al. 2010). In these studies, the value of NDVI is a relative measure of the amount of greenness and photosynthetic biomass of forests.

It has been widely recognized that climate change has an important influence on landscape dynamics including forests dynamics (Crookston et al. 2010). Changing climate is associated with widespread changes in meteorological patterns and meteorological parameters (e.g., temperature and precipitation) become indicators of the climate change. As climate continues to change, the surface temperature is projected to rise over the 21st century and the heat waves will occur more often and last longer; At the same time, there are likely more land regions where extreme precipitation events will become more intense and frequent (Pachauri et al. 2014). Additionally, changes in precipitation might not be uniform over space. Pachauri et al (2014) have found that the high latitudes and the equatorial Pacific are expected to experience an increase in annual mean precipitation; in many mid-latitude and subtropical dry regions, mean precipitation will likely decrease; and in many mid-latitude wet regions, mean precipitation will likely increase. Meteorological changes induced by the climate change have caused widespread impacts on landscapes, and from learning about which we could have a better understanding of the forest dynamics.

The US Gulf Coast region extends from Brownsville, Texas to the Florida Keys and encompasses a large variety of landscapes (Burkett. 2008). The forest composition around the Gulf Coast varies with substrate type, latitude/longitude, and aridity (Krauss et al. 2011). The climate change has a strong and direct impact on Gulf Coast forests through sea level rise, increased temperature, rainfall distribution variation and changes in frequency and intensity of extreme climate conditions: hurricanes, floods, droughts and tropical storms (Merem et al. 2012; Burkett. 2008; Day et al. 2008; Desantis et al. 2007; Mills and Andrey. 2002; Harcombe et al.1999; Michener et al.1997). The meteorological impact on the Gulf Coast forests differs by regions. For instance, precipitation in the spring and summer was found to be positively related to longleaf pine growth in Gulf of Mexico coastal plain (Henderson and Grissino-Mayer. 2009). While forests located within eastern Texas and Louisiana was found to be a function mostly of temperature (Cook et al. 2001). Understanding potential effects of climate change on Gulf Coast forests is therefore of critically importance from a meteorological perspective.

One of the critically important aspects of studies on forest dynamics is the application of correlation and regression analysis to examine landscape forest dynamics in relation to meteorological factors, such as precipitation and temperature. However, the use of relationship modelling to study faces (at least) two fundamental challenges. First, meteorological factors obtained in different scales or observed in diverse scenarios are expected to exhibit distinct impacts on the environment. Therefore, it is extremely difficult to establish an identical correlation between certain meteorological factors and environment over large space, even if it were possible to accurately discern meteorological changes impacts and to precisely model the environment responses. In particular, it was believed that spatial and temporal heterogeneity are critical to the understanding of underlying impacts of meteorological changes at different scenarios and scales (Ackerly et al., 2010; Elmendorf et al., 2012). The second issue is that given the complex nature of meteorological changes, they interact in myriad ways with forest landscapes. Because of the imperfect knowledge of current climates or the lack of awareness of potentially important variables, models are intrinsically uncertain, and the application of modelling is frequently overshadowed by uncertainties that arise in model parameterizations.

The regression analysis includes a set of statistical methods that are always employed to explain why different phenomenon occur and predict spatial outcomes. Evaluating impacts of meteorological changes is inherently difficult and yet of significant importance. The complexity in the understanding of the underlying meteorological changes poses substantial challenges. For instance, the spatial analysis needs to face two general problems: spatial autocorrelation (i.e., spatial dependence) and spatial non-stationarity (Zhang et al. 2009; Zhang et al. 2008; Shi and Zhang. 2003; Anselin and Griffith. 1988). Spatial autocorrelation represents correlations among neighbors over space (Zhang et al. 2008). The spatial autocorrelation in the error term might cause the violation of the independence assumption, which could lead to a biased estimation of the variance (Zhang et al. 2009). Spatial non-stationarity refers to a structural instability that model parameters vary systematically over space (Anselin 1990; Anselin and Griffith. 1988). In the face of these challenges, a diversity of approaches is needed. For instance, the geographically weighted regression (GWR) approach was developed to provide solutions to investigate the spatial relationship between variables. Moreover, the linear mixed-effects model (LMM) method was developed to model the spatial covariance structure in the data and which has been proved to be able to remove the effects of spatial autocorrelation to obtain more accurate estimates (Zhang et al. 2009; Breidenbach et al. 2007; Littell et al. 2006). It is because of that OLS method yields biased and inefficient estimates (Anselin. 1988), it was always taken as a benchmark when investigating other models (Zhang et al. 2009).

There has been a considerable number of studies extensively explored how changes in meteorological characteristics render vegetation dynamics in different spatial scales from local (Halper et al, 2012; Zhang et al, 2010) to global (Piao et al, 2014; Jong et al, 2013) and most of which were studying on landscapes influenced by extreme precipitation and temperature. For instance, a well-established relationship between meteorological characteristics and vegetation properties have been developed in Inner Mongolia, China (Chuai et al, 2013; Yang et al, 2012). It was found that in Inner Mongolia, NDVI correlated differently with temperature and precipitation, with obvious temporal differences and time scale of 80-day is the most significant and suitable for evaluating the vegetation dynamics to meteorological factors. Moreover, Qinghai-Tibetan Plateau, China was found to be characterized by a strong correlation between NDVI and meteorological factors, with variations in relation to the vegetation type and seasonality (Zhang et al, 2013; Piao et al, 2011; Zhong et al, 2010). However, there are still little remains known about the forest dynamics and underlying meteorological changes in the coastal areas, especially the Gulf of Mexico coastal region (**Fig**. 1.1).

Soils typically have adequate nutrient stocks to construct forest biomass (Murphy and Bowman. 2012) and soil was believed to be the foundation of the forest system (Schoenholtz et al. 2000). Several studies have shown the existence of soil effect on forests. The forest growth has been found in relation to soil water deficits (Michelot et al. 2012), soil fertility (Toledo et al. 2011) and soil drainage (Schoenholtz et al. 2000). Soil texture also appears to be important to forest ecosystems. For instance, the soil texture influences aboveground net primary production (ANPP) by controlling soil water availability. In humid areas, fine-textured soils with high water-holding capacities reduce water losses that occur through drainage below the rooting zone of plants, and support greater production (Epstein et al. 1997). Soil texture impacts on many hydrologic and biogeochemical processes in forest ecosystem by influencing retention of carbon, water, and nutrient ions (Silver et al. 2000; Jenny 1980).

This study aims to investigate forest dynamics to meteorological changes from three aspects: 1) By using statistical regression methods to model forest dynamics, this study firstly attempts to answer such a question as: if meteorological factors (i.e., precipitation and temperature) are the two factors that significantly explain alteration of forest landscapes and how the landscape dynamics was influenced spatiotemporally by them; 2) Given the fact that different vegetation types response differently to meteorological changes (Mao et al., 2012), this study will compare model performance from several different forest types and assess the capability of soil texture to explain forest dynamics that cannot be adequately explained by meteorological factors; and 3) this study will developed linear mixed-effects models (LMMs) for understanding of forest dynamics to the potential impacts from both fixed-effects and random-effects induced by meteorological factors.

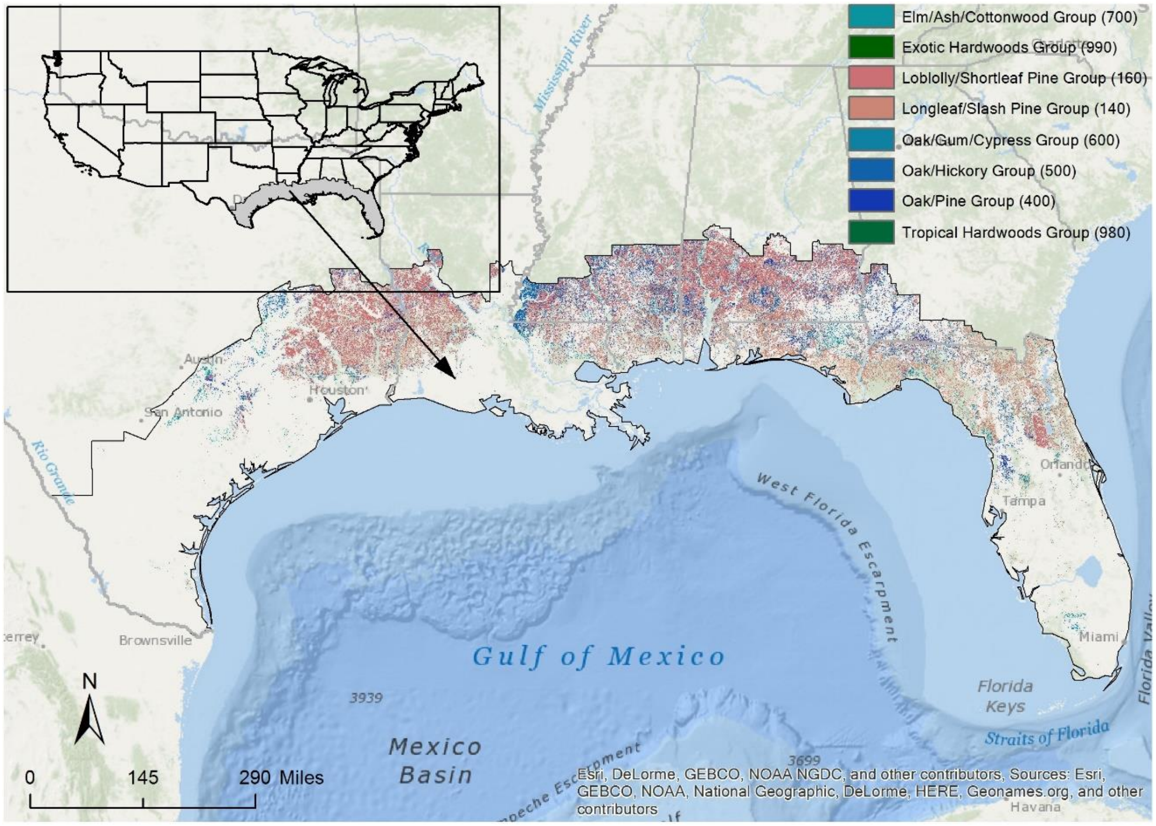

Figure 1.1 The geographical distribution of GOM coastal region

The Gulf of Mexico (GOM) coastal region consists of all counties located at a 100-miles landward buffer from Gulf of Mexico coastline (including coastal boundaries of five states located in the United States portion of the Gulf of Mexico region: Texas, Louisiana, Mississippi, Alabama, and Florida).

CHAPTER II

FOREST DYNAMICS TO PRECIPITATION AND TEMPERATURE IN THE GULF OF MEXICO COASTAL REGION

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Literature Review

Global climate change in the recent decades has emerged as one of the major factors affecting physiological and biophysical characteristics of vegetation. There is a growing body of studies direct toward modeling and analyzing dynamic vegetation response to rapid climate change, which suggests that seasonal behaviors of plants, such as emergence and senescence, are closely related to climate pattern shifts (Gordo and Sanz 2010; Krishnaswamy et al. 2014; Forkel et al. 2015; Estiarte and Peñuelas 2015). For instance, when it is getting warmer, growing season is expected to start earlier in the spring and survive longer into the fall (Baumol and Blinder 2015). Several global and regional studies have indicated that fluctuation of climate affects plant growth in diverse ways (Wu et al. 2011; Jong et al. 2013; Pravalie et al. 2014; Zhao et al. 2015; Bornman et al. 2015). It was believed that most plants are frequently sensitive to effects of two specific climate conditions: precipitation and temperature.

The recent studies showed that precipitation is the main driver for most ecological processes in vegetation system (Hilker et al. 2014; Zhao et al. 2015; Pravalie et al. 2014;

Hao et al. 2012; Paudel and Andersen 2010). However, differences of rainfall patterns can lead to spatiotemporal divergence in vegetation responses to precipitation, and

different vegetation has significant response to precipitation. In more detail, variations in amount and timing of precipitation may not keep the magnitude of precipitation effect consistent through all seasons (Nischitha et al. 2014; Otto et al. 2014; He 2014; Liu et al. 2011; Fensholt and Rasmussen 2011). Specifically, some ecological effects of climate are largely dependent on rainfall especially in summer (Chikoore and Jury 2010). In addition, it is also demonstrated that vegetation types did not have a uniform response to rainfall and thus vegetation responses could not be represented by an identical global model (Omuto et al. 2010; Richard et al. 2012).

Temperature is a dominant driving factor for vegetation growth and its correlation with vegetation dynamics has obvious global differences (Chuai et al. 2013; Piao et al. 2014). For instance, the correlation between temperature and vegetation growth is negative in low latitude during summer, while a positive correlation was found in high elevations at the beginning of growing season (Karnieli et al. 2010). Typically, agriculture areas are characterized by statistically significant relationships between temperature and plant growth (Na et al. 2010). Moreover, the influence of temperature could be hampered by strong topography (such as altitude and terrain orientation) when controlling greening patterns (Peters et al. 2012).

To make inferences about the condition of plant growth, remote sensing of vegetation is needed. Satellite remote sensing offers an efficient means of systematically obtaining vegetation information over large spatial and temporal scales. Research on vegetation cover detection and measurement has been conducted since the early 1980s

(Kirdiashev et al. 1979). Since it is closely related to chlorophyll/carotenoid ratio, the value of NDVI is an important indicator of vegetation activities, and thus it could provide information about the timing and progression of plant development (Yang et al. 2010). Through its reliable quality, MODIS (moderate resolution imaging spectroradiometer) NDVI product enables scientific analysis of plant growth with spatially and temporally consistent coverage. The assessment of vegetation coverage using MODIS NDVI product has been implemented by numerous studies successfully (Hao et al. 2012; Peters et al. 2012; Otto et al. 2014; Nischitha et al. 2014; Li et al. 2013).

Although there has been a considerable number of studies extensively explored how changes in precipitation or temperature render NDVI dynamics, neither of which was reported to have a dominant role. For instance, precipitation was found to be the most important factor that affects NDVI changes in Northwest China (Duan et al. 2011), whereas the NDVI – temperature correlation was found stronger than NDVI – precipitation correlation in most study sites located in Northeast China (Mao et al. 2012). There is a more specific case where either of those two factors has an individual influence on NDVI, which is however not the same for all ecoregions across a study area (Gao et al. 2012; Ghobadi et al. 2013).

Even though relationships between climatic factors and vegetation biophysical properties could be found in many global and regional studies, the effect of climate change on forests is still poorly understood within GOM (Gulf of Mexico). GOM encompasses temperate and tropical climate and provides multiple habitats for wildlife. A number of studies indicate that GOM coastal environment is among the most biologically diverse ecosystems (Peet and Allard. 1993; Sherrod and McMillan 1985; Noel et al.

1998). Occupied by high amounts of forest, vegetation regions characterized by diverse plant communities constitute a major terrestrial ecosystem in GOM coastal area, where fluctuations in precipitation and temperature bring about periodic changes to the local environment every year.

This study explored two climatic parameters, precipitation and temperature, that were derived from gridded dataset recorded over the period from March (2012) to February (2013), designed two linear regression methods geographically weighted regression (GWR) and ordinary least square (OLS) and applied them to evaluate spatiotemporal characteristics of forests and their implicit links with climate change. By monitoring NDVI changes, this study attempted to answer a question that precipitation and temperature are the two main causative factors, which drive forest growth and spatiotemporally influence forest growth changes.

Study Area

This study focused on measurement of climate change on GOM coastal forests. The GOM coastal forests were defined within a 160.9 km (i.e., 100 miles) inland buffer from Gulf of Mexico coastline (including coastal boundaries of five states located in the United States portion of the Gulf of Mexico forests: Texas, Louisiana, Mississippi, Alabama, and Florida). The combined coastline of this region is about 2,700 km (1,680miles) with an area of approximately 500,716.94 km^2, around 5% of U. S's territory and extending from latitude 24°57'22.953" N to 32°32'55.734" N and longitude from 80°3'3.280" W to 100°12'51.898" W. The study area is located within an extent that experiences warm temperate and equatorial climate (Kottek et al., 2006). Both of temperature and precipitation over this region are unimodal and have significant inverted-

U shapes (**Fig**. 1). Annual average temperature ranged from 12.6 °C to 28.0 °C with July being the hottest month and February the coldest month. Average monthly precipitation was about 118.7 mm. The most abundant rains were recorded in August, with an average of 194.5 mm, while November was the driest month, with only 30.0 mm of precipitation.

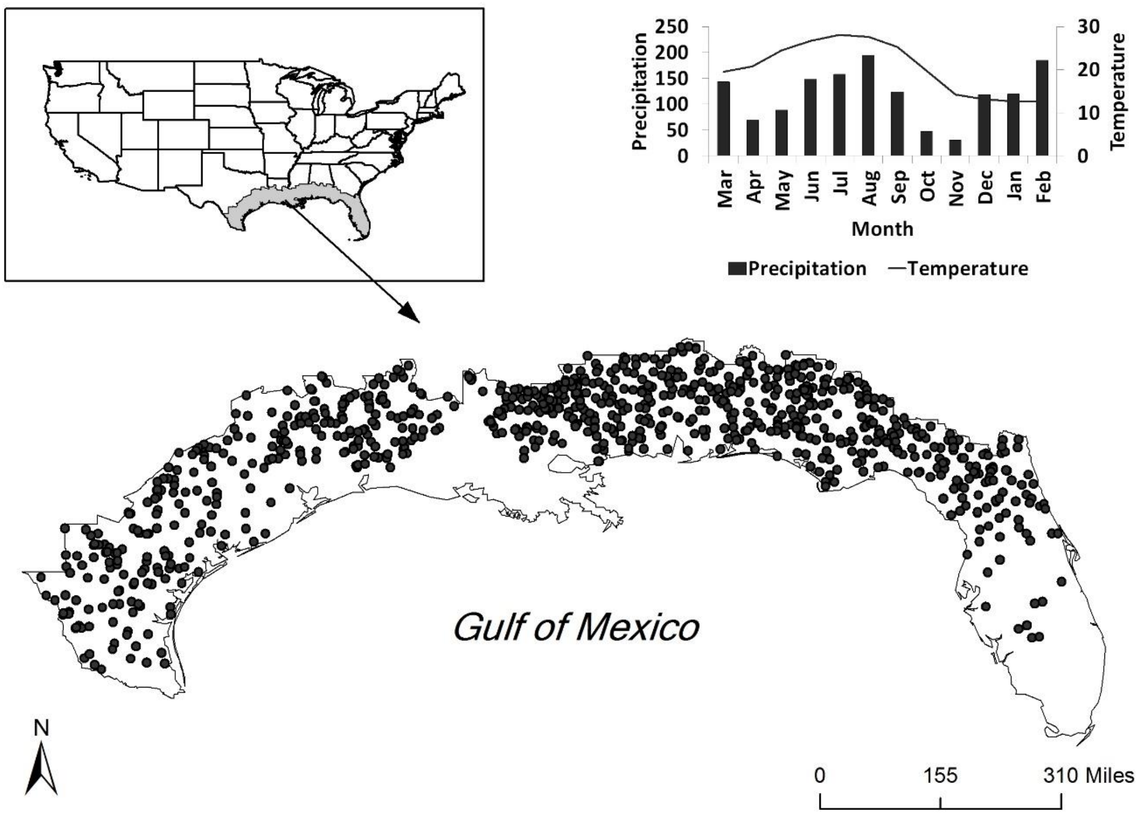

Figure 2.1 Monthly precipitation (mm) and temperature (°C) at randomly sampled coastal forest sites.

Data and Variables

Explanatory Variables: Precipitation and Temperature

Precipitation and temperature were chosen for two reasons: Firstly, as a result of periodic occurrences of several climate conditions, climate change could influence vegetation activities. However, it is often hard to fully determine all the climatic conditions affecting vegetation and even harder to qualify their effects. Thus, precipitation and temperature are the two variables only to be selected based on their availability. Secondly, as the pattern of photosynthetic activity is a function of precipitation and temperature and both of those are necessary for plants converting carbon into biomass, the development of greening pattern is thought to be largely dependent upon precipitation and temperature (Yamori et al. 2014). Monthly meteorological data (from March 2012 to February 2013) were obtained from a geographically referenced precipitation and temperature database, which was developed by the NRCS National Water and Climate Center (NWCC) partnering with Oregon State University (OSU). These datasets were generated as spatial climate products using PRISM (parameter-elevation regressions on independent slopes model) climate mapping system. The PRISM model outputs interpolated grid data and the value of these gridded data could be potentially related to climate state (Daly et al. 2002).

Dependent Variable: NDVI

Detection of vegetation was built on characteristics of NDVI. NDVI is closely related to the level of photosynthetic activities of plants (Yang et al. 2010). As one of the primary indicators measuring vegetation coverage, NDVI can be applied to observe trends of forest variations. The MODIS on board the NASA Terra satellite provides the 250-m resolution NDVI product which was utilized as a base to extract vegetation information from March (2012) to February (2013). The MODIS NDVI data were originally aggregated to 16-day composites using maximum NDVI compositing techniques to minimize the effect of off-nadir pixels and cloud contamination (Swets et al. 1999). All the data had already been geometrically corrected and provided by NASA (The National Aeronautics and Space Administration) on its website (http://modis.gsfc.nasa.gov/). For this research, monthly NDVI data were generated from the 16-day composites.

Combined and Extended Dataset

All the values of variables above were extracted from gridded data and compiled into an attribute table linked with point features. Point features were created by series of sampling points generated randomly and originally located within forests with NDVI larger than 0. Forested wetlands will not be considered in this research since their greening patterns were found insensitive to local precipitation change but more susceptible to water charge in the river system and overland runoff (Propastin et al. 2008). NDVI values and corresponding precipitation and temperature of 12 months were assigned to each point firstly. As mentioned, NDVI will be regressed on precipitation and temperature in different temporal scales. However, the averaged value of precipitation across four seasons or the entire year might not necessarily result in the highest correlations, and most likely better result can be obtained when precipitation is accumulated over a season or a year (Propastin et al. 2008; Liu et al. 2013). For this reason, the attribute table was adapted by adding accumulated precipitation values over four individual seasons and 1 year, which were constructed based on the monthly data. Methodologically, meteorological data and NDVI data were managed and analyzed using ArcGIS (ArcMap, version 10.1 ESRI Inc., Redlands, CA, USA).

Statistical Analysis

Modeling Methods

The great interest of this research was to uncover the impact of both temperature and precipitation on GOM coastal forest dynamics. With regard to dealing with this subject, linear regression methods were utilized to regress NDVI against temperature and precipitation. Since it is unclear how spatial non-stationarity impacts on the relationship between NDVI and temperature/precipitation, there should be a consideration about the two cases, non-stationarity and stationarity, separately. To completely understand a relationship and its potential variations, by far the most common types of linear regression methods achieving this aim are GWR and OLS. GWR is defined as the use of regression models by accounting for the impacts of variables as a presence of spatial non-stationarity in spatial data analysis (Foody 2003). OLS was utilized to observe how dependent variable responses to the alternation of explanatory variables from a regional perspective.

Ordinary Least Squares

Initially, attributed to its location independence and spatial stationarity, OLS model provides global relationship estimates. It could be written as follows:

$$\mathrm{y}_i = \alpha + \sum_{j=1}^{n} x_{ij}\,\beta_j + \varepsilon_i \tag{2.1}$$

Where, the two variables are y, the dependent variable, which represents NDVI, and x, the explanatory variables, which are climatic factors (precipitation and temperature). i indicates the i^{th} observation in a dataset, while, j represents the j^{th} explanatory variable. It was assumed that the same stimulus from either precipitations or temperatures provokes the same variation of NDVI anywhere in the study area. Therefore, regression parameters α and β were treated to be stationary over the whole study region. ε_i is normally distributed.

Geographically Weighted Regression

The theoretical background and applicability of GWR to explore spatial relationship have been deeply explained by the previous studies (Fotheringham et al. 2003; Brunsdon et al. 1998). The basic idea behind this regression method is to consider the variability of relationship spatially. The equation of GWR model is always proposed below.

$$y_i = \alpha(u_i, v_i) + \sum_{j=1}^{n} x_{ij}\, \beta_j(u_i, v_i) + \varepsilon_i \qquad (2.2)$$

By taking the superior aspect of GWR method, it was assumed that relationships between NDVI and climatic factors are not constant over analysis space. In other words, it is incorrect to hold that geographical areas occupied by vegetation respond identically to the same unit of precipitation or temperature at all study sites. Therefore, regression parameters α and β were estimated at each geographical location defined by two spatial coordinates u and v. Unlike conventional OLS, GWR method works in a way that each data point is assigned a weight inversely proportional to its distance from the regression point, thereby it can be written in matrix notation as follows:

$$\hat{\beta}_j(u_i, v_i) = (X^T W_i(u_i, v_i) X)^{-1} X^T W_i(u_i, v_i) y_i \qquad (2.3)$$

$$w_i = \begin{bmatrix} w_{i1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & w_{in} \end{bmatrix} \qquad (2.4)$$

Where, W_i is weighting matrix and given in Eq. (2.4), Among which w_i refers to the weight of i^{th} data point. Within a fixed distance, the near observation will be weighted a value of w_i more heavily than more distant ones. w_i could be calculated by the Gaussian weighting function which is given by the following:

$$w_{ij} = e^{-\frac{1}{2}\left(\frac{d_{ij}}{b}\right)^2} \tag{2.5}$$

Where d_{ij} is the distance between the i^{th} data point and location j. b is the bandwidth.

Where d_{ij} is the distance between the i^{th} data point and location j. b is the bandwidth.

R-squared value (coefficient of determination) runs from 0 to 1 and can be calculated to quantify how well the model could explain the variation of the dependent variable y, which performs as Eq. (2.6) and $s_{yy} = \sum(y - \bar{y})^2$.

$$R^2 = \frac{S^2{}_{xy}}{S_{xx}S_{yy}} \tag{2.6}$$

The p-value (t-test) for each estimated regression coefficients can be examined to determine if they are statistically significant or not. It is always set at a 5% significance level. The equation to get a t-test statistic is presented below:

$$T = \frac{\hat{\beta}}{s/\sqrt{s_{xx}}} \tag{2.7}$$

Where, $\hat{\beta} = \frac{s_{xy}}{s_{xx}}$, $s_{xy} = \sum(x - \bar{x})(y - \bar{y})$, $s_{xx} = \sum(x - \bar{x})^2$.

Results.

Results of OLS Modeling

The OLS approach was run for three rounds on the same dataset but with different variables, the first and second testing precipitation and average temperature against NDVI, respectively, and the third testing the joint effect of those two factors on NDVI. In each round, models were run 17 times for three different temporal scales, namely for 12 individual months, four individual seasons, and 1 year separately. Results of modeling (R^2 values) are summarized in **Fig**. 2.2. The statistical significant importance of all correlation statistics can be judged by a p-value of 0.05. The multicollinearity was not found in the explanatory variables while the variance inflation factor (VIF) indicated that two explanatory variables (i.e., precipitation and temperature) are not correlated (VIF < 7.5) (**Table** 2.1).

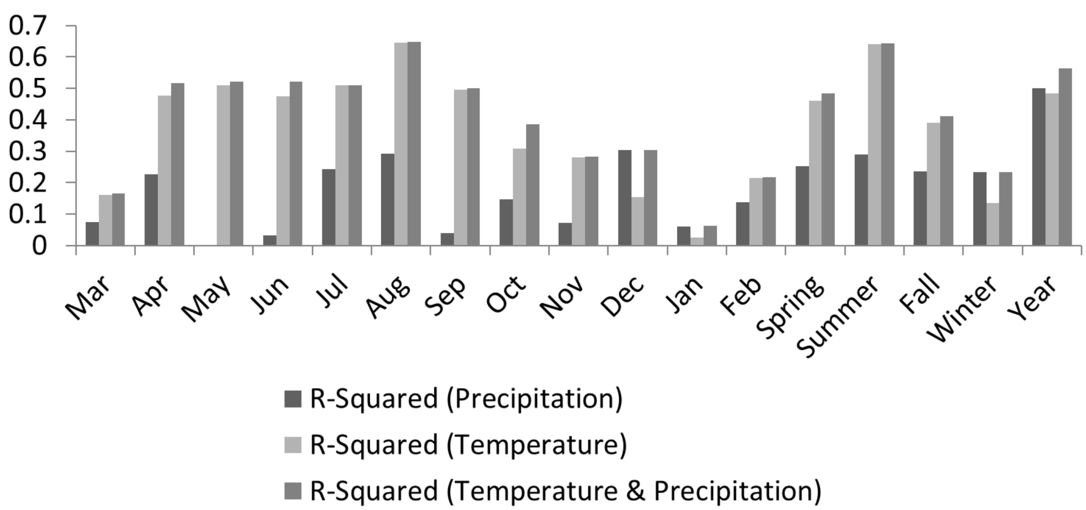

Figure 2.2 The R^2 values from regression analyses

In regression analyses, NDVI was regressed against precipitation, temperature, and joint effect from precipitation and temperature, respectively. All retained explanatory variables are significant at 5% level for calibration and validation

Table 2.1 Variance inflation factor (VIF) statistics for OLS regressing NDVI against precipitation and temperature

	VIF		VIF		VIF
March	1.45	Spring	1.44	Year	2.29
April	1.22				
May	1.01				
June	1.38	Summer	2.01		
July	1.92				
August	1.94				
September	1.03	Fall	1.55		
October	1.04				
November	1.53				
December	1.96	Winter	2.48		
January	2.05				
February	2.19				

The explanatory variables with VIFs larger than about 7.5 should be removed from the regression model.

Relationship between NDVI and Precipitation in Regional Scale

The R^2 value was deemed as the major index indicating if there is a dependence of NDVI on meteorological parameters. The result (**Fig**. 2.2) shows that variability in precipitation was not effective in explaining the variance of NDVI given the relatively poor R^2 values. R^2 value peaks at 0.30 in December, whereas none of the other 11 months has a value above 0.30. The seasonal varying precipitation could account for more variance in summer (R^2 value is 0.29) than in other three seasons. The R^2 value, which was derived from regression analysis modeling annual precipitation, is 0.50.

Relationship between NDVI and Temperature in Regional Scale

When compared with models utilizing precipitation, temperature appeared to be more effectively explaining the variance of NDVI during the same period. It shows that seasonal vegetation activities occurred in synch with temperature changes, and there was a stronger correspondence between temperature and NDVI during a period from spring to fall than in winter. It was also found that the continuously increasing temperature starting from spring did not drive R^2 value up to its peak in July. The maximum value of R^2 value (0.65) is associated with the second highest temperature (27.6 °C) of the year in August. This finding suggests that although being with the highest value of 28.0 °C, the temperature in July did not influence forests with the strongest magnitude. Actually, it has been clearly demonstrated that high temperatures of summer can cause plants to go dormant, which would be the most plausible explanation for the occurrence that the peak of temperature and R^2 value were in different months (Wu et al. 2011; Yamori et al. 2014). By contrast, photosynthesis slows at low temperatures, which may explain why temperature rarely impinges on plant growth in winter. Intuitively, R^2 values in winter months fluctuating around 0.20 reflected this.

Relationship between NDVI and Joined Effect of Temperature and Precipitation

The result of the multivariate analysis revealed that vegetation is sensitive to meteorological changes in most months (**Fig**. 2.2). Monthly precipitation and temperature could explain variance with an R^2 value of 0.65 (August) as the maximum and 0.06 (January) as the minimum. It shows that the lowest R^2 value (0.23) occurred during winter compared with spring (0.48), summer (0.64), and fall (0.41), which suggests that forests in the other three seasons were affected by rainfall and temperature much more than in winter. During winter, the air temperature lowers the temperature inside plants and causes all the process of photosynthesis to move slower, making it more difficult for rainwater (or possible snow water) to be absorbed by roots. Meanwhile, resulting from the absence of heat in molecular level, it is not easy for molecules to get involved in a biochemical reaction. These two processes are the main causes for photosynthesis dropping to a very low level during winter, which was believed to be related to NDVI decreasing. Consequently, vegetation was insensitive to varying precipitation and temperature, which gave rise to the lowest value of R^2 in winter.

Results of GWR Modeling

Theoretically, OLS regression method could reveal a relationship from a global or regional perspective but hides the local variability at the same time. It was believed that relationships would exhibit non-stationarity when the statistical analysis was "scaled down" to a local scale (Foody 2004; Propastin 2009). In order to find out what degree the observed trend of NDVI activity was driven by the effect of precipitation and temperature in a relationship characterized by non-stationarity, GWR method was employed on a local scale. By using GWR method, relationships observed by OLS models were amplified, which enabled a local examination of impacts of meteorological variables.

Precipitation in Local Scale

In order to find how much variance in NDVI can be explained by local variability in precipitation, I used GWR method when carrying out regression analysis on these two variables. Local R^2 values were derived from GWR models and were mapped in **Fig**. 2.3. Over the entire spring, higher R^2 values were mainly concentrated in a small part of Texas. The area with relatively higher R^2 values tended to expand northward in summer. In fall, the distribution of higher R^2 values did not vary distinctly but with an enormous decrease in magnitude. During winter months, more areas in Texas could be observed with higher R^2 values. Generally, all the four seasons were characterized by clustering of higher R^2 values which were mainly distributed in the west.

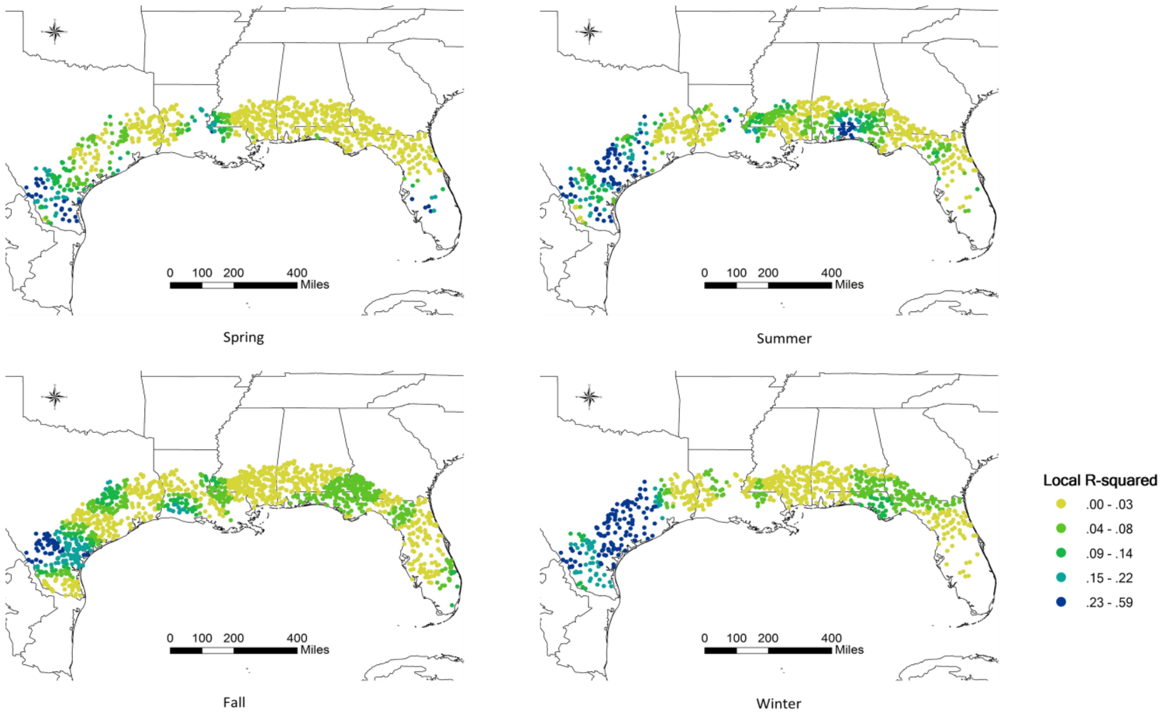

Figure 2.3 R^2 map of modeling NDVI against precipitation

The spatial changes of R^2 values (NDVI against precipitation) in a year from March (2012) to February (2013). Here, I employed multiple-color scheme for R^2 value displaying.

Temperature in Local Scale

It shows how fluctuations of NDVI were driven by local variation of temperature in **Fig**. 2.4. Higher R^2 values were firstly found in part of south Texas during spring. The region located in south Texas, where NDVI was observably affected by temperature variations, scarcely changed its extent in summer and then underwent shrinkages during fall and winter.

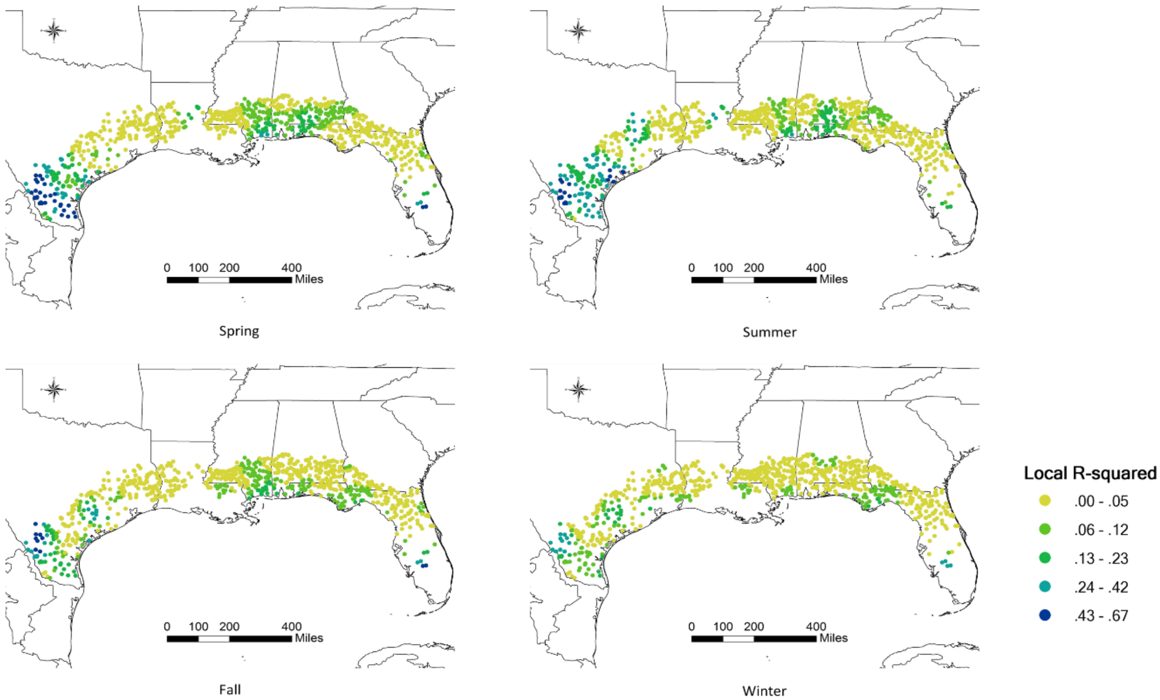

Figure 2.4 R^2 map of modeling NDVI against temperature

The spatial changes of R^2 values (NDVI against temperature) in a year from March (2012) to February (2013). Here, I employed multiple-color scheme for R^2 value displaying.

Joint Effect of Precipitation and Temperature

Across the whole study area, only the western part responded continuously and sensitively to the variation of compound effect from precipitation and temperature (**Fig.** 2.5). It indicates that the local variation of joined effect from meteorological change could explain generally more than half of the variance in NDVI of western part.

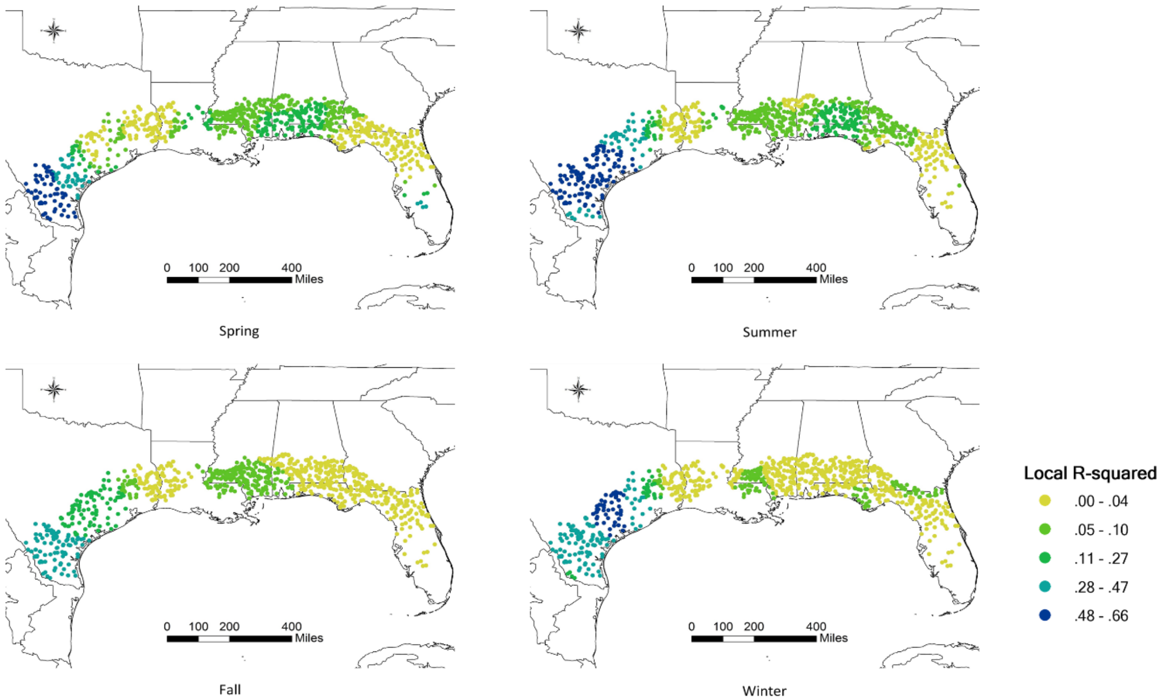

Figure 2.5 R^2 map of modeling NDVI against precipitation and temperature

The spatial changes of R^2 values (NDVI against precipitation and temperature) in a year from March (2012) to February (2013). Here, I employed multiple-color scheme for R^2 value displaying.

Discussions

This study focuses on the monthly, seasonal, and annual modeling between forest NDVI and precipitation and/or temperature. I used OLS and GWR to examine how precipitation and temperature impact on the forest dynamics that are characterized by the indicator NDVI. The R^2 values are mainly used to explore the relationship that is fitted using models as summarized above. Although modeling performance is not an objective of this study, **Table** 2.2 is provided below, which shows typically higher R^2 values are corresponding to lower AIC (Akaike information criterion) values and lower RMSE values. Residual plot and Q-Q plot are also checked for both OLS and GWR models, and assumptions of linear regression are satisfied.

Table 2.2 AIC, RMSE, and R^2 for OLS and GWR modeling with annual data

		R^2	*AIC*	*RMSE*
OLS	Precipitation	0.500	− 2008.26	0.0751
	Temperature	0.485	− 1982.56	0.0762
	Precipitation and temperature	0.563	− 2121.74	0.0702
GWR	Precipitation	0.741	− 2491.49	0.0541
	Temperature	0.741	− 2491.99	0.0540
	Precipitation and temperature	0.748	− 2500.76	0.0534

AIC: Akaike information criterion; RMSE: root mean square error.

Role of Different Explanatory Variables

The nature of the regional effect of meteorological variables can be judged by inspection of R^2 values from outputs of regression models. In general, monthly temperature appeared to be a more important explanatory variable than precipitation. OLS analysis revealed a relatively strong and significant relationship between NDVI and temperature (average R^2 value equals to 0.41), while the variation of precipitation could only explain less NDVI variance (average R^2 value equals to 0.25). This finding disagrees with result of the study by Balaghi et al. (2008), which indicated that compared to temperature, precipitation played a dominant role in the explanation of NDVI variance. Moreover, according to several studies, precipitation was believed to have a strong effect on variation of vegetation (Wang et al. 2003; Foody 2003; Paudel and Andersen 2010; Fensholt and Rasmussen 2011; Li et al. 2013; Wertin et al. 2015). Therefore, there is no particular reason to doubt that precipitation may exhibit a strong effect on forests within the study area. However, the connection between precipitation and NDVI seems counterintuitive in this study. This irregular finding can be attributed to the high proportion of forest coverage. Referring to the vegetation map derived from the national land cover database (Homer et al. 2012), a high occupation of forests is located in an area extending from Florida to eastern Texas. Receiving more than 120 mm of rainfall and having a temperature of 15 to 30 °C in most months of a year, this richly vegetated area is rarely affected by large climate volatility. Additionally, tree root system is capable of holding a great deal of moisture that can be released over time, which makes trees grow without being immediately affected by varying precipitation and extremely dry seasons. Thirdly, impacts of rainfall were found to be weak in humid/sub-humid areas (Li et al. 2004; Wang et al. 2003; Propastin et al. 2008; Fensholt and Rasmussen 2011; Richard et al. 2012; Wertin et al. 2015). Considering the fact that the study area is also mainly characterized by humid subtropical climate, it could explain why there was only a weak NDVI – precipitation relationship observed to explain the variance of NDVI.

This study focuses on the effects on forest dynamics driven by the significantly changing temperature and precipitation under the global warming/climate changes. Using MODIS 1-year data products of NDVI with the PRISM temperature and precipitation data, I statistically and spatially model the impacts of temperature and precipitation on forest dynamics, which is measured by NDVI. NDVI is a relative and indirect measure of the amount of photosynthetic biomass and therefore is highly correlated to biophysical parameters such as vegetation biomass and the fraction of green vegetation cover that follows annual cycles of vegetation and forest activities (Goward et al. 1985; Sellers 1987; Myneni et al. 1995; Birky 2001; Boelman et al. 2003; Meng et al. 2007; Verbesselt et al. 2010; Zhao et al. 2011; Li and Fox 2012). Birky (2001) used 1-year NDVI and a growth model with climate variables of light intensity, temperature, and moisture to analyze forest seasonal dynamics.

I analyze the monthly and seasonal forest dynamics caused by both precipitation and temperature. Monthly and seasonal forest dynamics plays a vital role in the Gulf Coast ecological conversation and natural resources management, since the Gulf Coast is experiencing significant physical and environmental changes driven by global warming and the severe weather in the Gulf region (Lott and Ross 2015).

Spatial Heterogeneity of Relationships

GWR models revealed spatial heterogeneities among relationships between NDVI and meteorological variables, which can be contributed to the diversity of patterns of precipitation and temperature. By regressing NDVI against annual temperature, it was found that samplings corresponding to high R^2 values tend to be fallen approximately in a 20.5 to 25 °C range (**Fig**. 2.6). It was believed that the chemical reaction of photosynthesis slows down at low temperatures and thus temperatures with low values presented weak capability to explain variance in their relationships with NDVI. A sharp decline around 900 mm of precipitation brought about two separate rainfall settings in plotting R^2 value against precipitation (**Fig**. 2.6). Approximately, R^2 was presented with larger values in a range from 300 to 900 mm than from 900 to 2300 mm. A similar finding has been illustrated quantitatively by a recent research, which suggested that this phenomenon could be explained by the diversity of vegetation rain-use efficiency and its high correlation with precipitation (Fensholt and Rasmussen 2011). Resulting from the distribution of precipitation and temperature, diversity of vegetation density also presented a correlation with observed spatial heterogeneity. Specifically, a large number of sampling sites were located within Texas, where higher R^2 values were related to lower NDVI values (**Fig**. 2.3). It was believed that those sparsely vegetated areas characterized by lower NDVI have small underground root systems, which may not hold moisture over a long time and result in strong sensitivities of their NDVI values to fluctuations in precipitation (Ferreira and Huete 2004). Vegetation was also found to be more sensitive to temperature in the late spring and summer; during which period, higher R^2 values were observed more distinctively in the western part than the other study sites (**Fig**. 2.4). This finding could be explained by a dominant role of temperature when controlling evapotranspiration during spring and summer (Munson et al. 2011).

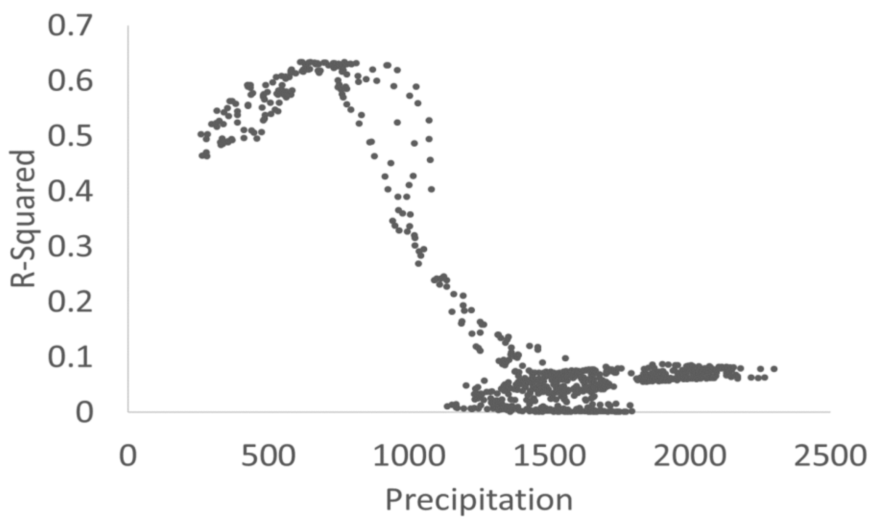

Figure 2.6 The relationship between precipitation (mm) against R^2 value

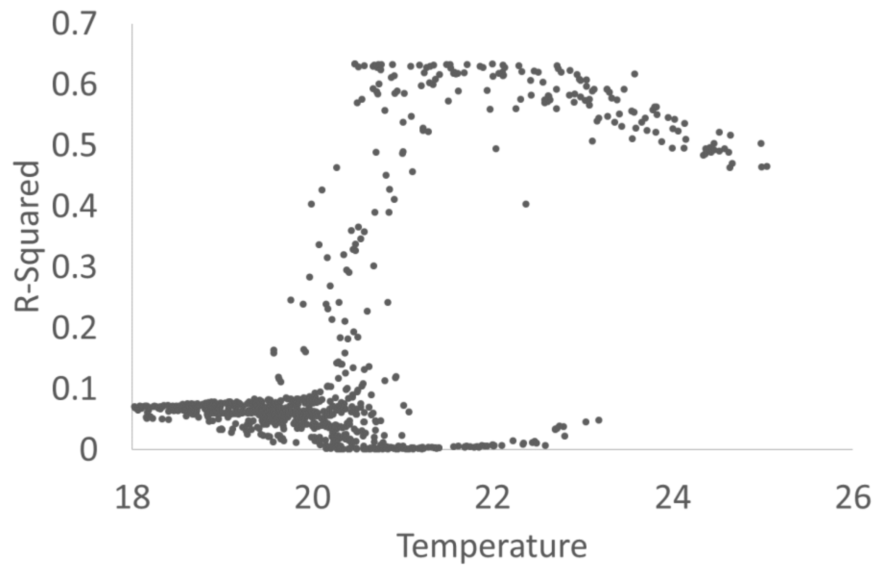

Figure 2.6 (continued) The relationship between temperature (°C) against R^2 value

Effect of Cumulative Precipitation

The precipitation cumulative effect was defined as an impact from precipitation amounts in the immediate few months prior to and including that of data acquisition or on an annual scale (Foody 2003). When NDVI was first regressed against monthly precipitation, it only displayed a weak strength of the NDVI – precipitation relationship in regard to a relatively small R^2 value (average equals to 0.14). As the time range was scaled down to a season or a year from a month, the question was then raised to what extent the accumulated precipitation might exert its effect on NDVI. The result shows that models, where NDVI was regressed against seasonal and annual cumulative precipitation, had some improvements in performance as R^2 value increased to 0.25 (seasonal level) and 0.50 (annual level). In other words, cumulative precipitation appeared to contain more information when explaining variations in forests. One possible explanation for this is that infiltration is a much longer process to store abundant shallow groundwater especially after heavy rainfall and it always takes time for water to replenish subsurface aquifers before a plant could imbibe moisture through its roots. As a result, vegetation response to a precipitation decrease (or increase) takes some time lags to be observed, which has been demonstrated in some regions (Yahdjian and Sala 2006; Fensholt and Rasmussen 2011; Höpfner and Scherer 2011; Richard et al. 2012).

Unexplained Variance

Even though the maximum R^2 value reached to 0.65 when regressing NDVI against monthly meteorological variables, a majority of derived R^2 values were below 0.5. It implies that the compound variability of precipitation and temperature could only explain a portion of the variance in NDVI. The remaining unexplained variance may be due to other factors which deserve more understanding. For instance, it has shown that plant growth is notably dependent on variations in soil type, soil moisture, rooting depth, and even topographic factors such as elevation or terrain orientation (Zhao et al. 2010; Piao et al. 2011; Richard et al. 2012; Peters et al. 2012; Lakshmi et al. 2013).

In a forest stand level, spatial heterogeneity could also play important roles in forest growth dynamics. Besides the two main factors of temperature and precipitation, soils often make significant contribution to forest yield, and therefore geostatistics (Zawadzki et al. 2005) and spatial econometric regression modeling (Meng et al. 2009) could be more effective in assessing the environmental contribution to forest dynamics. Geostatistics and spatial econometric regression are not suitable for the very sparsely sampled locations across the large GOM coastal region.

I did not include soil variables, which could be the reason to explain the unexplained variance. Soil moisture is closely related to or determined by precipitation and temperature and soil types can potentially influence forest dynamics and the vegetation index assessment from remote sensing (Zawadzki et al. 2016; Zawadzki and Kedzior 2014). Given specific sites at certain times, the assumption is reasonable and acceptable that it could be assumed that the contribution from soil to forest dynamics is relatively stable, and thus soil variables would not significantly change the contribution assessment of monthly and seasonal temperature and precipitation to forest dynamics, which is the focus of this study. This study did not consider forest growth and yield management, such as forest harvesting cycling in the coastal region, which also could potentially impact forest dynamics modeled with NDVI. I am going to conduct a study that further implores the coastal forest dynamics by grouping forest ecosystems into deciduous forest, evergreen forest, mixed forest, and plantations. Nevertheless, this study improved the understanding of how the forest dynamics was driven by varying precipitation and temperature on monthly and seasonal scales.

Conclusion

In this study, I proposed a biometeorology modeling approach of coastal forest dynamics and modeled the impacts of monthly, seasonal, and annual averages of temperature and precipitation on forest dynamics. Statistical regression models were designed to quantify regional and local impacts of meteorological changes on GOM coastal forests. Precipitation impact was found explicitly stronger as time range was scaled down from a month to a season or a year. Temperature appeared to be an important meteorological factor influencing forest growth, which could explain about

48% of the variation of NDVI in a year. The joint effect of precipitation and temperature presented a capability to explain 56% of the NDVI variance in a yearly model with cumulative monthly NDVI measurements. This capability exhibited an observable importance to forest dynamics in some months, while in others it was not.

Geographically weighted regression was proved to be a powerful tool for exploring spatial heterogeneity, and in this study, it offered the most locally explicit investigation of the spatially varying relationship between forest dynamics and meteorological changes. Precipitation and temperature presented a capability to explain 74% of the NDVI variance in a yearly model with cumulative monthly NDVI measurements. It was revealed that relationships between NDVI and meteorological factors were not strictly grounded on an identical magnitude but with spatially heterogeneous structures across GOM coastal forests. This finding suggests that the degree of control on NDVI depended on spatial patterns of precipitation and temperature. This study supported the applicability of both classic linear regression and geographically weighted regression methods and provided robust empirical evidence that regional meteorological changes significantly drive forest dynamics across the GOM coastal region.

CHAPTER III

DYNAMICS OF GULF COAST FORESTS IN RELATION TO METEOROLOGICAL FACTORS AND SOIL TEXTURE

Submitted for publication to Agricultural and Forest Meteorology.

Literature Review

Climate was believed to be the dominant driver of spatial variation in forest growth (Toledo et al. 2011). Gómez-Mendoza and Arriaga (2007) indicated that the long-term vegetation changes in the temperate forests of Mexico were deemed as a consequence of climate change. Climate change triggers phenology change such as spring leaf unfolding and radial growth through fluctuations in precipitation and temperature. Hilker et al (2014) have found that the vegetation canopy of the Amazon rainforest was highly sensitive to fluctuation of precipitation. It was suggested that vegetation growth in mid to high latitudes of North America is very sensitive to temperature change (Wang et al. 2011). Relationships between precipitation and forest dynamics have also been demonstrated by some studies (Zhao et al. 2015; Richard et al. 2012; Hao et al. 2012; Omuto et al. 2010), but it is still not clear of the different roles of temperature and precipitation. Additionally, the relationship between forest dynamics and meteorological factors is complex.

Despite the well-demonstrated importance of meteorological factors, soil properties could be related to forest vegetation characteristics (Levine et al. 1994). The complication of soil characteristics might also contribute to the relationship changing. For instance, it was believed that the variation in the relationship between vegetation and precipitation could be disturbed due to the influence of soil background (Chen et al. 2014; Kang et al. 2014). Forests depend on the availability of water and nutrients as essential resources for growth (Toledo et al. 2011). The soil condition plays an important role in the forest's ability to extract water and nutrients. Water and nutrient availability are likely to promote the formation of forest and tree growth (Murphy and Bowman, 2012). Soil water availability can be a major limiting factor for forest growth by influencing growth rates (Michelot et al. 2012; Toledo et al. 2011). Soil texture is one of the most fundamental qualitative soil physical properties that has the potential to influence water and nutrient availability (Schoenholtz et al. 2000; Epstein et al. 1997). The role of soil texture to soil quality is retention and transport of nutrients and water (Schoenholtz et al. 2000; Doran and Parkin. 1994). Soil texture influences the soil water flow, availability, storage and soil moisture (Kreutzweiser et al. 2008; Prepas et al. 2006; Bronick and Lal, 2005; Pachepsky and Rawls, 2003), which is a basic soil quality indicator used for comparing soil quality and a master soil property that influences most other properties and processes of soil (Schoenholtz et al. 2000). For example, soil texture strongly influences on many hydrologic and biogeochemical processes in forest ecosystems through its effects on belowground carbon storage, water availability and nutrient retention (Silver et al. 2000; Epstein et al. 1997; Jenny 1980).

Although the general relationship of forest dynamics and its explanatory variables has been widely studied, its spatial characteristics have not been modeled in the Gulf Coast. I proposed to use the geographically weighted regression (GWR) method incorporating multivariate into spatial modeling to quantify spatial relationships, as it can incorporate the spatial heterogeneity among data observations into parameter estimation (Zhang et al. 2009). Forest dynamics was influenced by individual or combined effects from meteorological factors (e.g., precipitation and temperature) and soil properties (Li and Meng, 2016; Kang et al. 2014; Usman et al. 2013; Di et al. 1994). For instance, it was found that rainfall, temperature, and soil fertility generally have positive effects on forest tree growth (Toledo et al. 2011).

Forests differ in their tolerance of and requirements from the environment so that their associations with underlying factors might vary as a function of environmental conditions (Swaine 1996). For instance, variations in the relationship between vegetation and its explanatory variables were known to be caused by spatial variations in surface properties such as vegetation type, soil type and land use (Usman et al. 2013). The variation in a relationship could be caused by the forest types. It has been demonstrated that temperature-vegetation relationship could vary with vegetation types (Chuai et al. 2013; Karnieli et al. 2010; Omuto et al. 2010). It was found by Michelot et al. (2012) that in a study area with three dominant forest types: beech, pine and oak, forest types differed in their dynamics to meteorological and soil conditions. Specifically, the beech growth was observed to be negatively correlated with maximal temperatures in June and July and positively correlated with precipitation from May to July; pine growth was sensitive to maximal temperatures and soil water deficits from June to August as well as positively correlated with precipitation from May to August; oak growth was strongly affected by June and July precipitations and positively correlated with the precipitation of the whole growing season.

By referring previous studies, it was known that climate has long been identified as the main factor that impacts on forest activities (Forman 1964; Box 1981; McKenney et al. 2007; Gómez-Mendoza and Arriaga. 2007; Toledo et al. 2011). Specifically, Mather and Yoshioka (1968) believed that climate impacts on vegetation directly through climatic factors such as precipitation and temperature, and indirectly through the effects that climatic factors have on soil conditions. Therefore, the hypothesis is that forest dynamics responds to both meteorological and soil, especially precipitation, temperature, and soil clay and silt in this study. Therefore, the objectives of the study are first, to understand the extent of dependence of forest dynamics on precipitation, temperature and soil texture, and second, to understand the differences in forest dynamics among 8 forest type groups in the Gulf Coast.

Study Area

The study was conducted in the Gulf of Mexico (GOM) coastal forest, which is an inland area situated within 160.9 km (i.e., 100 miles) of the Gulf Coast of the United States (**Fig.** 3.1). This region is mainly characterized by a wide range of forest types and extending from Florida to east Texas. The warm temperature and equatorial climate (Kottek et al. 2006) are mainly distributed over the study area, with an average annual temperature of 19.0 ° C and an average annual precipitation of 144 mm. The temperature amplitude is relatively not high: average February temperature is below 8.0 ° C and average July temperature is about 27.7 ° C.

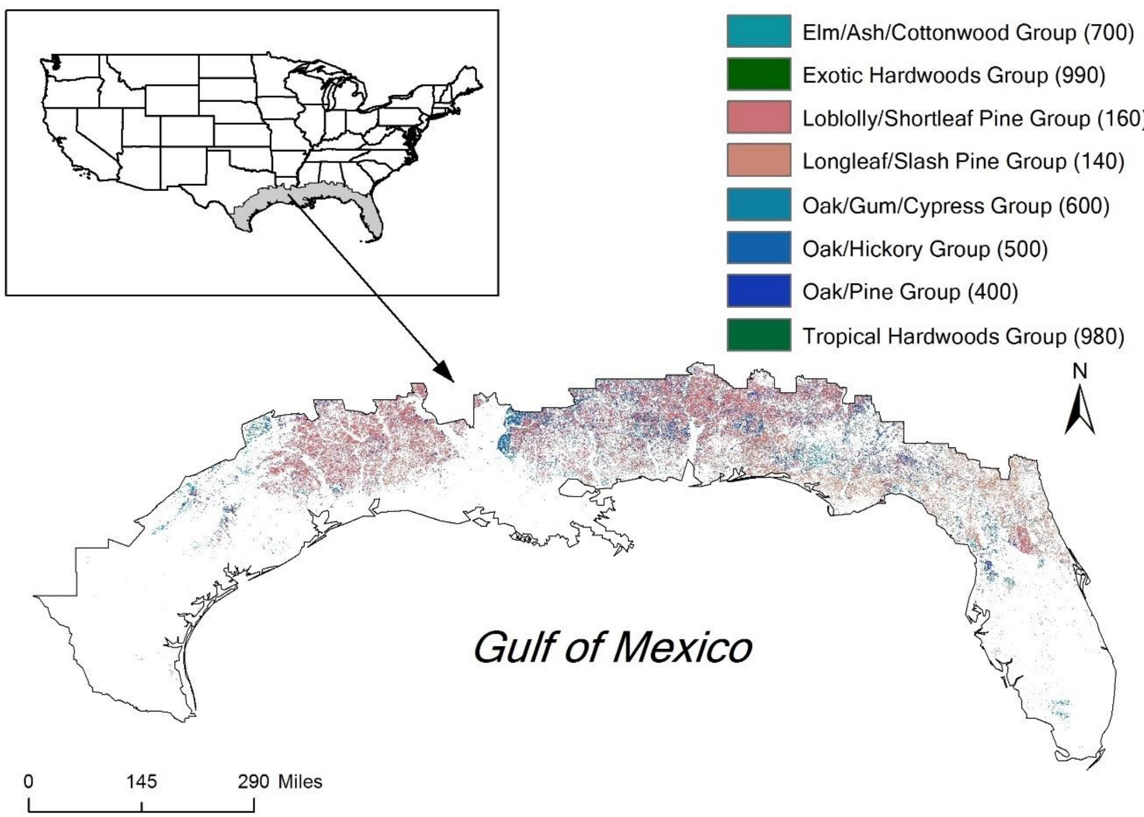

Figure 3.1 Study area: the Gulf of Mexico (GOM) coastal forests.

The study area consists of 11 distinct forest type groups. The forest type group was defined by the national forest type dataset (https://data.fs.usda.gov/geodata/rastergateway/forest_type/), and each of which was coded with a three-digital number (e.g., '700' represents a forest type group of Elm/Ash/Cottonwood).

Data Source

Normalized Difference Vegetation Index (NDVI)

The NDVI is commonly utilized based on the contrast between vegetation and soil, and it was used in this study as a phenology indicator of forest growth. The NDVI was demonstrated well-correlated with biophysical parameters (e.g., vegetation biomass and the fraction of green vegetation cover) and photosynthetic forest activities (Myneni et al. 1995; Birky 2001; Boelman et al. 2003; Meng et al. 2007; Verbesselt et al. 2010; de

Jong et al. 2011; Leon et al. 2012; Li and Meng, 2016). The forest dynamics in this study was represented by remotely sensed data derived from MODIS NDVI (MOD13Q1) product (https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table/mod13q1). The MODIS NDVI gridded data at 250-meter spatial resolution were acquired between March 2009 and February 2010 from the Land Processes Distributed Active Archive Center (LP DAAC). By using a 3x3 moving-window function with a mean filter, I first removed noisy pixels that were anomalously characterized by high or low pixel values relatively to their neighboring pixels (Propastin and Kappas. 2008). The 16-day NDVIs were integrated to averaged values for each of the analysis months and seasons. Four meteorological seasons were defined as spring (March, April, May), summer (June, July, August), autumn (September, October, November) and winter (December, January, February) (Trenberth. 1983). The monthly and seasonal meteorological data was then resampled from its native 250m × 250m to a resolution of 4km × 4km.

Meteorological Data

The photosynthetic activity is a function of precipitation and temperature, which are necessarily important for the forest to convert carbon into biomass (Yamori et al. 2014). Given to the fact that it is hard to fully determine and qualify all the meteorological factors potentially related to forest dynamics, the meteorological data in the study consist of monthly precipitation and temperature. Values of monthly precipitation and temperature were originally extracted from PRISM (parameter-elevation regressions on independent slopes model, http://prism.oregonstate.edu/) dataset. The monthly PRISM climate data were originally collected and developed by the U.S.

Department of Agriculture NRCS National Water and Climate Center (NWCC) partnering with Oregon State University (OSU). Preparation of seasonal temperature was made by averaging monthly data; while the seasonal precipitation was accumulated by monthly data over a three-month period. Seasons of both temperature and precipitation consists of four periods made up of three months each, which coincided with those of NDVI data.

Soil Data

Soil texture is one of the basic soil properties that would change little through time for a given soil (Schoenholtz et al. 2000). Therefore, in this study soil texture was taken as a relatively stable variable. The Gridded Soil Survey Geographic (gSSURGO) database provides a gridded map layer derived from the vector layer, tabular data containing information about soil properties and a value-added look up table. The soil texture is commonly determined by proportions of three components: sand, silt, and clay in the soil (van Breemen et al. 1997). Based on the gSSURGO dataset, soil texture information was extracted from attributes of ‘sandtotal_r’, ‘claytotal_r’ and ‘silttotal_r’, which were a series of ‘representative values’ representing the percentage of sand, clay and silt components, separately. The three measures of the soil texture are not independent (Swaine 1996). To avoid problems with multicollinearity, two components (silt and clay) will be used instead of the original three.

Forest Type Groups

The GOM coastal forests are described as 11 type groups, which was defined by the national forest type dataset (https://data.fs.usda.gov/geodata/rastergateway/forest_type/). The dataset was developed by the USFS Forest Inventory and Analysis and Forest Health Monitoring programs and the USFS Remote Sensing Applications Center, and totally 28 forest type groups across the contiguous United States are mapped.I first randomly generated 500 sites for each forest type group. Temperature, precipitation, soil texture, and NDVI values at all sampled sites were organized by compiling them into an individual attribute table for each forest type group.

Statistical Analysis

A detailed description of the theoretical background and applicability of GWR have been given by previous studies (Li and Meng, 2016; Fotheringham et al. 2003; Brunsdon et al. 1998). As a local regression technique, GWR considers the variability of relationship spatially and could help to overcome the non-stationarity problem. By using GWR method, the relationship between response variable y_i and its explanatory variable x_i was calculated for every point. The models were developed as:

$$y_i = \alpha(u_i, v_i) + \sum_{j=1}^{n} x_{ij}\,\beta_j(u_i, v_i) + \varepsilon_i \tag{3.1}$$

where u and v are two spatial coordinates; regression parameters α and β were estimated at each geographical location (u_i, v_i); ε_i is the random error term; n is the number of explanatory variables.

In order to analyze the individual and compound effect of temperature, precipitation and soil texture on NDVI separately at the seasonal level, I fitted five simple or multiple regression models (**Table** 3.1) for every season from March 2009 to February 2010. Simple linear regressions were performed between NDVI and precipitation, temperature and soil texture, respectively in model 1, model 2 and model 3. Both precipitation and temperature were then included in a multiple regression analysis against NDVI in model 4. To obtain a more comprehensive analysis of the compound effect of all explanatory variables, I related NDVI to four independent variables (precipitation, temperature, percentage sand, and percentage clay) in model 5. For each forest type groups, the simple and multiple linear regressions were performed.

Table 3.1 Five fitted models by regressing NDVI (y_i) against explanatory variables.

1	*Precipitation* model	x_{i1} = precipitation
2	*Temperature model*	x_{i1} = temperature
3	*Soil model*	x_{i1} = percentage of clay; x_{i2} = percentage of silt
4	*Meteorology model*	x_{i1} = precipitation; x_{i2} = temperature
5	*Meteorology-soil model*	x_{i1} = precipitation; x_{i2} = temperature; x_{i3} = percentage of clay; x_{i4} = percentage of silt

All the regression models worked in the way that all data points that located within the region defined around a regression point were weighted by their distances from that regression point. Therefore, the matrix form of parameter estimation for *i* was given as:

$$\hat{\beta}_i(u_i, v_i) = (X^T W_i(u_i, v_i)X)^{-1} X^T W_i(u_i, v_i) y_i \tag{3.2}$$

$$w_i = \begin{bmatrix} w_{i1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & w_{in} \end{bmatrix} \tag{3.3}$$

where β_i is the parameter at location *i*; w_i is the weighting matrix whose diagonal element refers to the geographical weight associated with site *j* at which measurements were made for regression point *i*.

The weighting function used in this study is expressed as below:

$$w_{ij} = e^{-\frac{1}{2}\left(\frac{d_{ij}}{b}\right)^2} \tag{3.4}$$

where d_{ij} is the distance between locations of regression point *i* and site *j (the surrounding points of i)*, and *b* is bandwidth.

To properly reflect the relationship between NDVI and explanatory variables, I used R^2 (coefficient of determination) values to evaluate the performance of models. The R^2 value obtained from regression modeling accounted for the percent of the variations in NDVI explained by models. A general rule is that the higher the R^2 value is, the more a model could explain the variation of the response variable. It performs as Eq. (3.5)

$$\mathrm{R}^2 = \frac{S^2{}_{xy}}{S_{xx}S_{yy}} \tag{3.5}$$

where $\mathrm{s}_{yy} = \sum(y - \bar{y})^2$.

In addition to the R^2, Akaike information criterion corrected (AIC) and residual sum of squares (RSS) are two measures of regression model performance. AIC is the relative measure of goodness of fit. RSS is the measure of discrepancy between observed data and the estimated model. Models characterized by lower AIC values and lower RSS values typically have better performances (Fotheringham et al. 2003; Brunsdon et al. 1998).

The *P*-value (t test) is statistically expressed as the examination of estimated regression parameters, which could be used to determine if regression parameters are statistically significant or not. It is always set at a 5% significance level. The equation for t-test statistic is expressed as:

$$T = \frac{\hat{\beta}}{s/\sqrt{s_{xx}}} \tag{3.6}$$

where $\hat{\beta} = \frac{s_{xy}}{s_{xx}}$, $s_{xy} = \sum(x - \bar{x})(y - \bar{y})$, $s_{xx} = \sum(x - \bar{x})^2$.

Results.

Seasonal Modelling of Forest Dynamics

The result showed that the R^2 value varied within a wide range from 0.133 to 0.952 (**Table** 3.2) and all the explanatory variables were linearly and significantly ($p < 0.05$) correlated with NDVI.

Table 3.2 Coefficient of determination (R^2) values for seasonal modeling of forest dynamics

		Longleaf Slash Pine	Loblolly Shortleaf Pine	Oak Pine	Oak Hickory	Oak Gum Cypress	Elm Ash Cottonwood	Tropical Hardwoods	Exotic Hardwoods
Model1	Spring	0.251	0.256	0.280	0.319	0.224	0.623	0.515	0.528
	Summer	0.260	0.285	0.254	0.419	0.224	0.705	0.497	0.601
	Fall	0.198	0.133	0.208	0.212	0.134	0.417	0.456	0.292
	Winter	0.222	0.135	0.225	0.229	0.181	0.167	0.421	0.365
Model2	Spring	0.232	0.261	0.277	0.309	0.211	0.611	0.529	0.520
	Summer	0.302	0.294	0.292	0.422	0.223	0.707	0.494	0.577
	Fall	0.207	0.135	0.218	0.190	0.142	0.419	0.487	0.272
	Winter	0.238	0.137	0.251	0.206	0.181	0.174	0.404	0.407
Model3	Spring	0.258	0.307	0.348	0.328	0.276	0.653	0.550	0.546
	Summer	0.302	0.335	0.339	0.434	0.271	0.734	0.519	0.606
	Fall	0.253	0.196	0.289	0.224	0.209	0.477	0.505	0.287
	Winter	0.292	0.184	0.287	0.219	0.223	0.265	0.430	0.432
Model4	Spring	0.295	0.282	0.321	0.334	0.240	0.630	0.574	0.560
	Summer	0.351	0.310	0.313	0.441	0.251	0.721	0.542	0.605
	Fall	0.258	0.160	0.271	0.232	0.172	0.449	0.523	0.335
	Winter	0.263	0.164	0.276	0.254	0.203	0.201	0.495	0.425
Model5	Spring	0.350	0.358	0.427	0.364	0.315	0.673	0.640	0.598
	Summer	0.418	0.379	0.410	0.473	0.318	0.757	0.610	0.647
	Fall	0.334	0.252	0.405	0.280	0.253	0.512	0.619	0.380
	Winter	0.359	0.241	0.381	0.284	0.268	0.328	0.575	0.480

Model 1: precipitation model; Model 2: temperature model; Model 3: soil model; Model 4: meteorology model; Model 5: meteorology-soil model.

The precipitation model (model1) was performed by regressing NDVI against precipitation. The R^2 ranged from 0.133 to 0.705 with the lowest value found in Loblolly/Shortleaf Pine forests, and the largest value found in Elm/Ash/Cottonwood forests. Summer appears to be a season with the largest R^2 value and winter appears to be with the lowest R^2 value.

The R^2 values obtained from temperature model (model2) with temperature as the only explanatory variable were observed to vary from 0.135 to 0.948. The seasonal values of R^2 exposed that spring and summer are the two seasons with relatively higher R^2 values than fall and winter.

In soil model (model3), R^2 values were observed to vary significantly among forest type groups. Elm/Ash/Cottonwood group was characterized by the largest R^2 value; while Loblolly/Shortleaf Pine group was characterized by the lowest R^2 value.

The ability of meteorology model (model4) to explain the variance of NDVI was changed by forest type groups. The variation of summer NDVI in Elm/Ash/Cottonwood forests was the best explained by the meteorology model (R^2 = 0.721); while NDVI of fall Loblolly/Shortleaf pine forests was found to be least explained by the meteorology model (R^2 = 0.160). The seasonal R^2 derived from meteorology model was undergoing a slightly increase from spring to summer and a decrease from summer to winter.

The R^2 value was calculated for the meteorology-soil model (model5) considering the compound effect of precipitation, temperature and soil texture, with the largest value (0.757) found in Elm/Ash/Cottonwood forests and lowest value (0.241) found in Loblolly/Shortleaf Pine forests. Moreover, the meteorology-soil model exhibited higher

R^2 values than model1, model 2, model3 and model4, which implies that the meteorology-soil model best fitted the data.

Annual Modelling of Forest dynamics

The R^2 value obtained for modeling of annual forest dynamics was presented in **Table** 3.3. For most forest type groups, R^2 values obtained from precipitation models approximately equal to values of R^2 derived from temperature models, which suggests the relatively equivalent magnitude of changing precipitation and temperature for explaining NDVI variance in forests. Actually, there are several mechanisms by which meteorological factors could influence forest dynamics: the finding obtained by Zhao et al (2010) indicated an equivalent role of precipitation and temperature in explaining variation in NDVI. Within some vegetation systems, precipitation was identified as the dominant factor affecting forest dynamics, and the temperature may play a minor role (Zhao et al. 2015; Hilker et al. 2014; Pravalie et al. 2014; Hao et al. 2012); while in other cases, temperature was considered as the main driving factor related to vegetation activities (Pravalie et al. 2014; Piao et al. 2014; Chuai et al. 2013).

The soil model exhibited relatively high R^2 values (> 0.500) explaining the variance of NDVI in some forests type groups such as Elm/Ash/Cottonwood, Tropical Hardwoods and Exotic Hardwoods. It was believed that soil texture is an important factor correlated to forest dynamics by influencing water-holding capacities and water infiltration rates (Michelot et al. 2012). Soil texture could also affect soil inherent fertility which is a limiting factor for controlling tree growth rate (Toledo et al., 2011). For instance, fine textured soils always have low infiltration rates that can contribute to the movement of nutrients adsorbed by soil particles (Kreutzweiser et al. 2008; Whitson et al. 2003).

In most forests, meteorology models explained the approximately equivalent variance of NDVI to soil models, according to a comparison of R^2 values obtained from these two types of models. The meteorology-soil model best fitted the data for all the forest groups, which implies that the observed variation in NDVI could be attributed to variations in all three explanatory variables: precipitation, temperature and soil texture.

Three groups of forests (Oak/Gum/Cypress, Longleaf/Slash Pine and Loblolly/Shortleaf Pine) occupying more than half of the study area, were found consistently with fewer variations of NDVI explained by all the designed models than other forest type groups. The forest-cover extent, forest distribution and decreases or increases in green biomass could be associated with forest harvest or regeneration (Drummond and Loveland, 2010; Wilson and Sader, 2002), and in other words, forest dynamics could be interrupted by human activities such as forest planting and timber harvesting; this might alter the forest species composition, structure, ecosystem processes, and landscape patterns (Chuai et al. 2013; Thompson et al. 2011; Bu et al. 2008; Bossel and Krieger. 1991). As a result, models with meteorological factors and/or soil texture could have limited effects on forest dynamics. Moreover, the evergreen needle forests (e.g., pine forests) with deep rooting systems were found less sensitive to climatic conditions (Immerzeel et al. 2009; Piao et al. 2004), which could explain the finding that Longleaf/Slash Pine and Loblolly/Shortleaf Pine appeared to be with relatively lower R^2 values in precipitation models, temperature models, and meteorology models.

Table 3.3 Comparison of annual model performance indicators (R^2, AIC and RSS)

		Longleaf Slash Pine	Loblolly Shortleaf Pine	Oak Pine	Oak Hickory	Oak Gum Cypress	Elm Ash Cottonwood	Tropical Hardwoods	Exotic Hardwoods
R^2	Model 1	0.229	0.165	0.209	0.268	0.150	0.551	0.469	0.475
	Model 2	0.215	0.170	0.246	0.261	0.139	0.538	0.473	0.479
	Model 3	0.256	0.232	0.305	0.279	0.202	0.592	0.509	0.486
	Model 4	0.278	0.188	0.271	0.284	0.172	0.559	0.513	0.514
	Model 5	0.350	0.279	0.404	0.312	0.243	0.617	0.597	0.560
AIC	Model 1	-1211	-1379	-1296	-1403	-1277	-1182	-784	-710
	Model 2	-1207	-1381	-1319	-1399	-1275	-1173	-790	-712
	Model 3	-1209	-1402	-1332	-1394	-1290	-1210	-787	-710
	Model 4	-1227	-1383	-1320	-1404	-1281	-1184	-796	-725
	Model 5	-1242	-1413	-1377	-1397	-1296	-1222	-817	-741
RSS	Model 1	1.121	1.029	1.206	1.028	1.041	0.937	0.792	0.734
	Model 2	1.141	1.023	1.150	1.038	1.054	0.965	0.786	0.727
	Model 3	1.081	0.946	1.060	1.012	0.978	0.852	0.733	0.718
	Model 4	1.050	1.001	1.112	1.006	1.014	0.921	0.727	0.679
	Model 5	0.945	0.888	0.909	0.967	0.928	0.799	0.602	0.615

Model 1: precipitation model; Model 2: temperature model; Model 3: soil model; Model 4: meteorology model; Model 5: meteorology-soil model.

The R^2 value map was then generated by model5 modeling annual NDVI of different forest type groups. R^2 values were compared and which were observed to vary significantly in the space over the study area. As outlined in **Fig.** 3.2, the west of the study region is mainly vegetated by Elm/Ash/Cottonwood and Exotic Hardwoods groups, which was characterized by relatively high R^2 values. Moreover, relatively high R^2 values were also found in areas occupied by Tropical Hardwoods forests. Lower R^2 values were found in forests dominated by Longleaf/Slash Pine, Loblolly/Shortleaf Pine and Oak/Gum/Cypress groups extending from east Texas to west Florida. Specifically, the western section of Oak/Pine and Oak/Hickory forests was featured by relatively higher R^2 values than the eastern section.

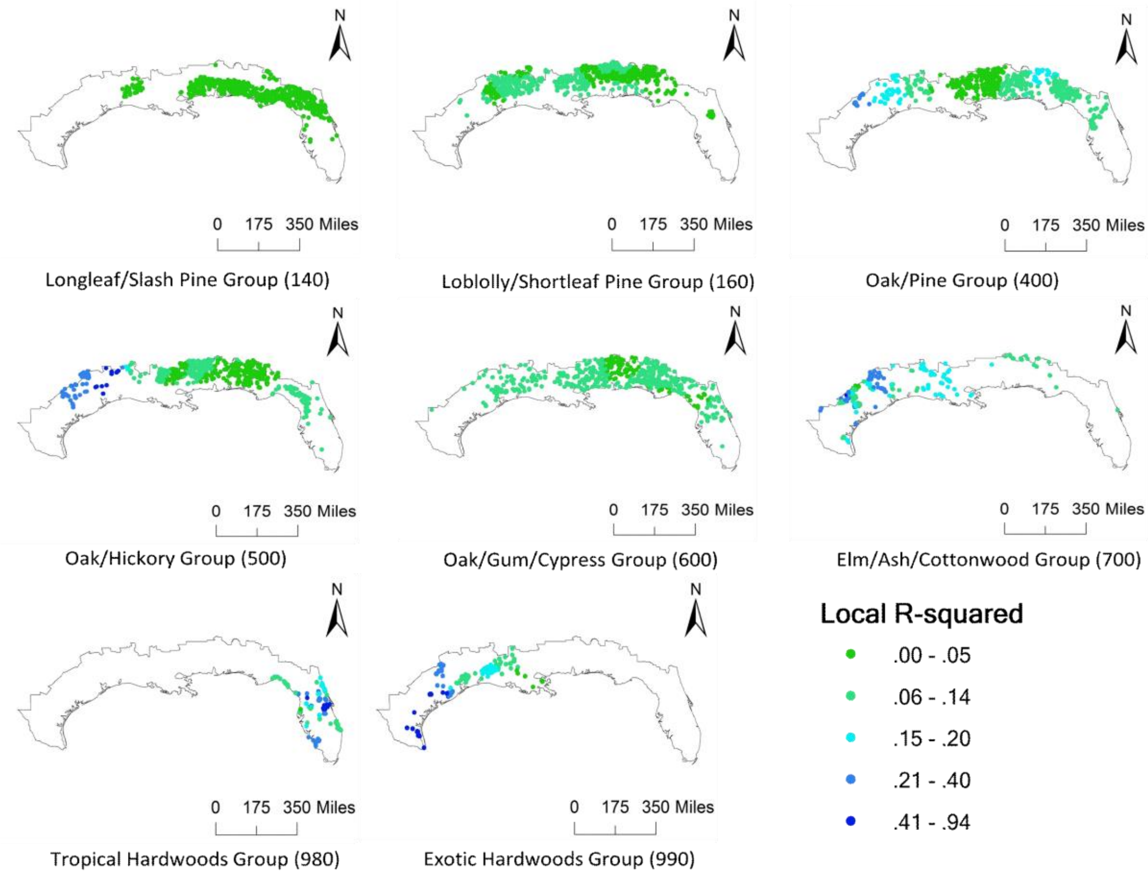

Figure 3.2 The spatial changes of R^2 values obtained from the annual meteorology-soil model.

Here, I employed a multiple-color scheme for local R^2 value displaying. The forest type group was coded with a three-digital number (e.g., '140' represents a forest type group 'Longleaf/Slash Pine').

The R^2 value distribution presented by **Fig.**3.2 was characterized by a spatial drift over the study area, which implies a large difference in the capabilities of meteorology-soil models explaining forest dynamics. This could be explained by the finding of previous analysis on forests showing that the forest types might differ in timing and magnitude of their correlations with meteorological variations (Zhao et al. 2015; Mette et al. 2013; Chuai et al. 2013; Michelot et al. 2012; Piao et al. 2004).

Discussions

Model Performance And the Role of Explanatory Variables

According to the observed higher R^2, lower AIC and lower RSS values (**Table** 3.3), soil models result in a better fit of data than precipitation models and temperature models for most forest type groups, which indicated that soil models could explain more of variance than precipitation and temperature models did. Similarly, as it was shown in **Table** 3.2, using soil as an explanatory variable in regression modeling resulted in slightly higher R^2 values than considering precipitation or temperature in regression models, which suggested that soil is acting more importantly than precipitation or temperature when explaining forest dynamics. Mather and Yoshioka (1968) have pointed that climate influences vegetation not only through meteorological factors (directly), but also through the effects that meteorological factors have on soil conditions (indirectly). However, for most studies related to forests, the soil was rarely considered for explaining forest dynamics. By developing soil models and comparing them with other models, this study highlighted an important role of soil in forest dynamics modeling.

R^2 (from both **Table** 3.2 and **Table** 3.3), AIC and RSS values of soil models and meteorology models were examined and compared, and it showed that meteorology models are generally characterized by better performances than soil models in four forest type groups (e.g., Longleaf/Slash Pine, Oak/Hickory, Tropic Hardwoods and Exotic Hardwood), which suggested a more important role of the meteorological factor to forest dynamics modeling than soil. In contrast, the soil model presented a generally better performance than the meteorology model in four forest type groups: Loblolly Shortleaf Pine, Oak/Pine, Oak/Gum/Cypress and Elm/Ash/Cottonwood, where the explanation of forest dynamics would have a higher dependence on soil than on meteorological factors. I speculated that the relative importance of soil and precipitation-temperature combination modeling forest dynamics varied by forest type groups.

By examining seasonal R^2 values (**Table** 3.2) and yearly R^2, AIC and RSS (**Table** 3.3) values, in all 8 forest type groups except for the Oak/Hickory, the meteorology-soil model showed the best overall fit with the highest R^2, lowest AIC and the lowest RSS values, which revealed the stronger explanatory power of precipitation, temperature and soil texture. Therefore, the meteorology-soil model is preferred as the best means of regression modeling of forest dynamics.

NDVI – An Indicator of Forest Dynamics

In this study, I use NDVI as a measurement indicator of forest dynamics, referring to the dynamics of canopy structure and phenology of forests, and for a given type of forests, seasonal and yearly NDVI values are applied to the quantification of its growth across the Gulf Coast. The forest dynamics has been studied and interpreted from various perspectives. In a study conducted by Giri et al (2007), forest dynamics refers to the forest deforestation and degradation. Moreover, forest dynamics also refers to the forest gap formation and closure (Yamamoto 2000; Bossel and Krieger. 1991). Generally, the study of forest dynamics is focused on changes in forest structure and composition arising from natural or anthropogenic forces (Pretzsch. 2009). Seasonal variations of NDVI were demonstrated to be related to vegetation phenology (McCloy and Lucht, 2004) and was used as a proxy for 'forest dynamics' (Soudani et al. 2012; Beck et al. 2006).

Explanatory Data Selection

Wang et al (2011) have conducted a research over a 9-years period (1989– 1997) in Great Plains of North America and found that during years with extreme climate conditions, the seasonal relations between meteorological factors (e.g., precipitation and temperature) and NDVI were quite different and complicated in different years. Additionally, variability in NDVI can be influenced by disturbances (e.g., hurricanes) (Neeti et al. 2012). Hurricane Katrina affecting Northern Gulf Coast region by landfall, flooding and the combination of both drought and increased salinity resulted in a reduction in NDVI (Rodgers et al. 2009), which might bring uncertainties into forest dynamics modeling. Therefore, I believed that studies conducted under extreme climate conditions might not reflect a general relationship between forest dynamics and its explanatory variables. By examining meteorological recordings ranging from 2002 to 2016, I excluded all the years with temperature extremes or erratic rainfall and eventually the year of 2009 was identified as the study period due to its intermediate precipitation and temperature values when compared to other historical recordings.

Conclusion

Using GWR method, I included precipitation, temperature and soil texture in regression modeling of their individual and combined effects on 8 forest type groups within the Gulf Coast and to compare their relative contributions to NDVI variations. R^2 values for regression models showed that both meteorological factors and soil could significantly explain NDVI variation in the Gulf Coast forests. Meteorology-soil models performed on Elm/Ash/Cottonwood forest explained more variations of NDVIs than on NDVIs of other forest type groups: Tropical Hardwoods, Tropic Hardwoods, Exotic

Hardwood, Oak/Pine, Longleaf/Slash Pine, Loblolly Shortleaf Pine, and Oak/Gum/Cypress. The GWR modeling also implied that the presence of heterogeneity in relationships over the study area was related to forest types, meteorology, and soil.

Model performance indicators (R^2, AIC and RSS) indicated that the performance of model fit was found to differ by forest type groups with different combinations of explanatory variables. The meteorology-soil model was demonstrated to be the best means of regression modeling for all the forest type groups except for Oak/Hickory forests. The soil model presented a better performance when explaining forest dynamics in following groups: Loblolly/Shortleaf Pine, Oak/Pine, Oak/Gum/Cypress and Elm/Ash/Cottonwood. However, Longleaf/Slash Pine, Oak/Hickory, Tropical Hardwoods, and Exotic Hardwoods forest groups were characterized by a better performance of meteorology model than soil models. The soil model was fitted better than precipitation model and temperature models for almost all the forest type groups.

CHAPTER IV

APPLICATION OF RANDOM EFFECTS TO EXPLORE DYNAMICS OF GULF COAST FORESTS IN RELATION TO METEOROLOGICAL FACTORS

Literature Review

A growing body of studies are carried out to explore climate change and its impact. Climate change is of fundamental importance to forest dynamics and there is a concerted effort to model spatial variations in vegetation caused by the changing climate (Propastin and Kappas. 2008). Vegetation systems are influenced by a massive amount of spatiotemporal contextual factors (Mather and Yoshioka, 1968; Cruz-Cárdenas et al. 2016). Meteorological factors vary over space and time and forest dynamics vary accordingly (Cruz-Cárdenas et al. 2016; Pacheco et al. 2010). As numerous scholars have noted, meteorological factors have the potential to facilitate forest growth (Galván et al. 2014; Babst et al. 2013; Prasad et al. 2008; Fekedulegn et al. 2003). Meteorological factors that drive forest dynamics were identified as two major variables: temperature and precipitation. Forest dynamics has been proved to be dependent on temperature (Wang et al. 2011; Vicente-Serrano et al. 2010). Karnieli et al (2010) have found that temperature is a significant independent variable relative to vegetation-cover variations and its impact varies with location, season, and vegetation type. Additionally, it was found that precipitation is a primary driver of forest dynamics (Vicente-Serrano et al. 2010). Under a changing climate, precipitation is predicted to be the most important environmental factor influencing phonological patterns in arid and semiarid areas (Zhao et al. 2015; Gómez-Mendoza et al. 2008; Moore et al., 2005). Li and Meng (2016) have examined the effects of precipitation on forest dynamics and found that seasonality of precipitation can influence forest dynamics.

In recent years, a variety of statistical techniques has been developed and utilized to quantify spatial relationships. The linear regression model is the most common form of statistical modelling and is applied in various fields of geographic applications (Propastin and Kappas. 2008). Some research have attempted to apply linear regression model to assess the relationship between vegetation system and meteorological factors (Li and Meng. 2016; Chuai et al. 2013; Piao et al. 2004). Much of this research is focused on detecting change patterns and trends by using fixed effect models such as OLS and GWR. For instance, Propastin and Kappas (2008) presented that the application of OLS regression model could provide an accurate estimation of the relationship between variables. However, OLS regression is not suitable for analyzing spatially correlated observation and measurements (Zhang et al. 2008). GWR models take spatial autocorrelation into account for estimating the model coefficients and better understand the non-stationarity in explanatory variables (Zhao et al. 2010; Zhao et al. 2015).

The method considering both fixed and random effects for coefficient estimation is known as the linear mixed-effects model (LMM) (Zhang and Borders. 2004). LMM is applicable to a diverse set of applications and domains, and is fundamental to spatial data science. The LMM provides an appropriate basis for the investigations of the spatial relationship between response and explanatory variables, highlighting spatial dependence and variation in modeling processes, estimating model coefficients, and identifying temporal changeability of the spatial relationship (Zhang et al. 2009; Zhang et al. 2008). The LMM is capable of characterizing the spatial covariance structures in the data with different geostatistical models, and obtaining more accurate predictions for the response variable than those derived from fixed-effects models (Littell et al. 2006; Breidenbach et al, 2007; Meng et al. 2007). Winter (2013) explains random effects as a factor that is usually nonsystematic and unpredictable, and would influence on the data. Therefore, it is necessary to understand how forest responses to explanatory variables were influenced by random-effects.

The Gulf Coast forest around the Gulf of Mexico is one of the most biologically diverse ecosystems, and which relies on favorable temperatures and appropriate precipitation patterns (Barrow et al. 2005; Noel et al. 1998; Peet and Allard. 1993; Sherrod and McMillan 1985). Variation in either temperature or precipitation, including earlier warm days for temperature or increased occurrences of extreme variability in rainfall, could impact on forest dynamics. It was documented that coastal forests are especially vulnerable to climate change (Barrow et al. 2005). As such, changes in temperature and precipitation within the Gulf Coast are and will consistently affect coastal forests. However, to our knowledge, there is a relative dearth of focus on studies of coastal forest dynamics to changing climate within the Gulf Coast. The Gulf Coast were dominated by the temperate forest, which was believed to be an appropriate study site for measuring climate variability (Gómez-Mendoza et al. 2008).

The aim of this study is to advance the spatial statistical thinking through utilization of the LMM. By using the precipitation, temperature and the normalized difference vegetation index (NDVI) data ranging from March (2009) to February (2010), this study intended to determine the importance of random-effects in explaining forest dynamics within the Gulf Coast, and to explore how seasonal changes in meteorological factors render forest dynamics at county scales. Based on statistical analysis, I expected that fixed and random effects from meteorological variables could play important roles in the modeling of forest dynamics. Specifically, this study is interested in answering two following questions: 1) if precipitation and temperature influence forest dynamics through both fixed and random effects, and 2) if forest dynamics to meteorological conditions vary across four seasons.

Study Area and Data Source

Study Area

The study was conducted within an inland buffer area located approximately 100 miles from the coastline of the Gulf of Mexico (**Fig**. 4.1.). An average annual precipitation of 144 mm and average annual temperature of 19.0 ° C characterize the climate as temperate continental. Temperatures range from 8.0 ° C to 27.7 ° C in winter and summer, respectively. The majority of precipitation occurs as rain through the whole year. The study area is occupied by a large forest extending from eastern Texas to the Florida Keys, which varies greatly due to the influence factors such as climate change and human disturbance (Barrow et al. 2005).

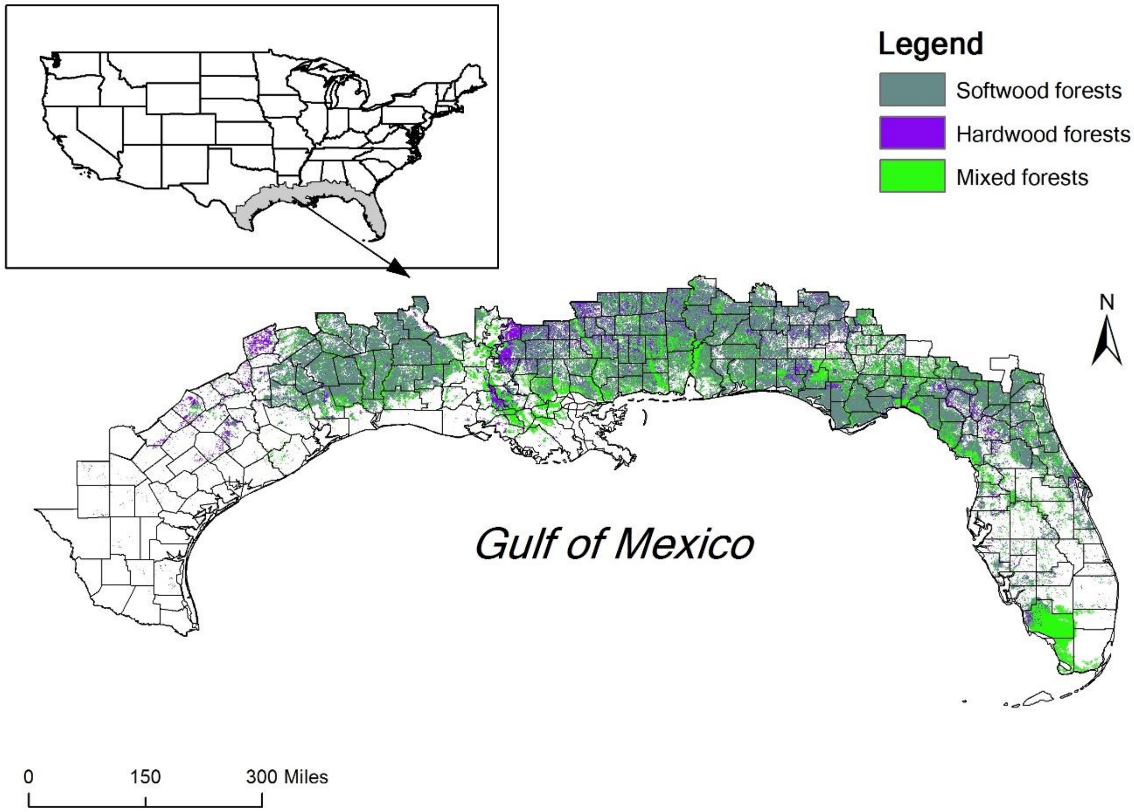

Figure 4.1 Study area: The Gulf of Mexico coastal region

Data Source

I collected meteorological data during a period from March (2009) to February (2010), including monthly precipitation and temperature from the PRISM (parameter-elevation regressions on independent slopes model, http://prism.oregonstate.edu/) dataset, which was produced by the NRCS National Water and Climate Center (NWCC) partnering with Oregon State University (OSU). The preparation of the seasonal (or yearly) temperature was made by averaging monthly temperatures over three months (over twelve months). The seasonal (or yearly) precipitation was generated by an accumulation of monthly precipitations over a corresponding season.

The Normalized Difference Vegetation Index (NDVI) is one of the most widely used multispectral vegetation indices in Remote Sensing. NDVI is formulated based on reflectance measurements in the red and near-infrared (NIR) portion of the spectrum. Forest biomass and dynamics characteristics could be represented by NDVI at the landscape scale (Zhao et al. 2015; Propastin and Kappas. 2008; Meng et al. 2007). Therefore, this study employed NDVI to quantify forest greenness and biomass. The NDVI data were obtained ranging from March (2009) to February (2010), using MODIS NDVI (MOD13Q1) products at 250-meter spatial resolution.

Both meteorological data (explanatory variables) and NDVI data (response variable) were originally raster layers and had to be converted to vector format of ArcMap to meet the requirement of regression modeling. Values of variables were extracted from original raster data layers to county-based polygons. In this study, a total of 244 polygons were used in regression analysis after removing invalid values.

Statistical Analysis

The linear mixed-effects model (LMM) is an expansion of the most basic statistical models, the linear regression model. In a mixed-effects model, the effects of the variable are assumed to be a random sample of a larger population that vary randomly around a population mean (Breidenbach et al, 2007). This is referred to as random-effects. An LMM can be written as a single combined model with fixed and random effects. The combined model is expressed as:

$$y_i = (\beta_{0i} + b_{0i}) + \sum_{j=1}^{n}(\beta_{1ij} * x_{ij}) + \sum_{j=1}^{n}(b_{1ij} * x_{ij}) + \varepsilon_i \qquad (4.1)$$

$$\varepsilon_i \sim N(0, \sigma^2)\ i.i.d \qquad (4.2)$$

$$\mathrm{b_{0ij}} \sim N\left(0, \sigma_{\mathrm{b_{0ij}}}{}^2\right)\ i.i.d \tag{4.3}$$

$$\mathrm{b_{1ij}} \sim N\left(0, \sigma_{\mathrm{b_{1ij}}}{}^2\right)\ i.i.d \tag{4.4}$$

Here β_{0i} and β_{1ij} are the fixed effect coefficients to be estimated from data; b_{0i} and b_{1ij} are the random effect coefficients; *i* is the *ith* observation; *j* is the *jth* variable. The random effects b_{0i} and b_{1ij} are assumed to be independent for different *i*; the ε_i of different *i* is assumed to be independent of the random effects.

Fixed effects are constant across individuals, and random effects vary. In essence, each county has its own random regression line such that the intercept is $\beta_{0i} + b_{0i}$ and the slope is $\beta_{1ij} + b_{1ij}$. The intercept and slope of the model could be assumed to vary randomly unit by unit (Meng et al. 2007; Hökkä 1997). Different types of models were developed: the random intercept model estimates separate intercepts for each unit at which the intercept is permitted to vary. Another type of random effect model, of which intercepts as well as slopes are allowed to vary, estimates separate slopes for each variable for each unit (**Table** 4.1.).

Table 4.1 Mixed Effects Modeling of Forest Dynamics

	Model Name	*Fixed-effect Variable*	*Random-effect Variable*
1	Random intercept and random meteorology-slope model	precipitation and temperature	precipitation and temperature
2	Random intercept and random precipitation-slope model	precipitation and temperature	precipitation
3	Random intercept and random temperature-slope model	precipitation and temperature	temperature
4	Random intercept model	precipitation and temperature	NA

To investigate relationships between NDVI and meteorological variables, seasonal and yearly NDVIs were regressed against precipitation and temperature. The mixed-effects approach allowed us to account for variation in NDVI by treating intercepts and slopes as random terms. Therefore, I proposed four options for the random configuration: (i) random intercept and random slopes of both precipitation and temperature; which included fixed coefficients, a random intercept and random slopes of both precipitation and temperature; (ii) random intercept and random slope of precipitation, which included fixed coefficients, a random intercept and a random slope of precipitation; (iii) random intercept and random slope of temperature, which included fixed coefficients, a random intercept and a random slope of temperature; (iv) random intercept, which included a fixed intercept, a random intercept and fixed slopes of both precipitation and temperature.

Results.

LMMs were performed between NDVI and meteorological factors. I included both precipitation and temperature in a multiple regression analysis against NDVIs. An intercept and slopes with respect to precipitation and temperature for both random and fixed effects were estimated in model1; in model2, an intercept and a slope with respect to precipitation for both random and fixed effects were estimated; in model3, an intercept and a slope with respect to temperature for both random and fixed effects were estimated; only an intercept for both random and fixed effects was considered in model4. The forests were classified into three forest types. For each forest type, linear regressions were performed and examined.

The overall model fitting was evaluated by three statistics including the coefficient of determination (R^2), Akaike information criterion (AIC) and Bayesian information criterion (BIC), which are usually presented as model comparison tools for mixed-effects models (Nakagawa and Schielzeth, 2013; Meng et al. 2007). The information criteria (e.g., AIC and BIC) were used to select the best models by comparing models relative to one another. The R^2 value obtained from regressions accounts for the percent of the variations in NDVIs explained by models. As the mixed-effects model yields two variances: a variance associated with random-effects and a residual variance, it is not entirely clear which to use when calculating R^2 values. Nakagawa and Schielzeth (2013) have derived two easily interpretable values of R^2. The marginal R^2 describes the proportion of variance explained by the fixed factor(s) alone, which is useful in identifying the most parsimonious model (Orelien and Edwards. 2008). The conditional R^2 describes the proportion of variance explained by both fixed and random factors (Orelien and Edwards. 2008). **Table** 4.2, 4.3 and 4.4 summarized the results of the linear mixed modeling softwood, hardwood and mixed forests NDVI against explanatory variables.

Table 4.2 AIC, BIC and R^2 for the fitted model of softwood forests

Model	*Season*	*AIC*	*BIC*	*R^2c*	*R^2m*	*p-Value*
Model1	Spring	-595.8	-581.1	0.61	0.49	<.0001
	Summer	-602.7	-588.0	0.57	0.48	
	Fall	-683.0	-668.3	0.56	0.40	
	Winter	-549.4	-534.7	0.41	0.04	
	Year	-656.9	-642.2	0.63	0.39	
Model2	Spring	-595.0	-580.3	0.59	0.49	
	Summer	-601.6	-586.9	0.53	0.48	
	Fall	-679.4	-664.7	0.50	0.40	
	Winter	-547.2	-532.5	0.39	0.04	
	Year	-653.9	-639.2	0.60	0.39	
Model3	Spring	-595.8	-581.1	0.61	0.49	
	Summer	-602.7	-588.0	0.57	0.48	
	Fall	-683.0	-668.3	0.56	0.40	
	Winter	-549.4	-534.7	0.41	0.04	
	Year	-656.9	-642.2	0.63	0.39	
Model4	Spring	-595.0	-580.3	0.59	0.49	
	Summer	-601.6	-586.9	0.53	0.48	
	Fall	-679.4	-664.7	0.50	0.40	
	Winter	-547.2	-532.5	0.39	0.04	
	Year	-653.9	-639.2	0.60	0.39	

Table 4.3 AIC, BIC and R^2 for the fitted model of hardwood forests

Model	*Season*	*AIC*	*BIC*	*R^2c*	*R^2m*	*p-Value*
Model1	Spring	-459.4	-444.6	0.67	0.36	<.0001
	Summer	-537.4	-522.6	0.62	0.58	
	Fall	-505.9	-488.2	0.54	0.13	
	Winter	-405.8	-391.0	0.61	0.01	
	Year	-513.7	-498.9	0.63	0.27	
Model2	Spring	-454.5	-439.7	0.63	0.36	
	Summer	-537.0	-522.1	0.59	0.58	
	Fall	-501.5	-486.6	0.48	0.13	
	Winter	-394.6	-379.7	0.54	0.01	
	Year	-506.9	-492.1	0.58	0.27	
Model3	Spring	-459.4	-444.6	0.67	0.36	
	Summer	-537.4	-522.6	0.62	0.58	
	Fall	-505.9	-488.2	0.54	0.13	
	Winter	-405.8	-391.0	0.61	0.01	
	Year	-513.7	-498.9	0.63	0.27	
Model4	Spring	-454.5	-439.7	0.63	0.36	
	Summer	-537.0	-522.1	0.59	0.58	
	Fall	-501.5	-486.6	0.48	0.13	
	Winter	-394.6	-379.7	0.54	0.01	
	Year	-506.9	-492.1	0.58	0.27	

Table 4.4 AIC, BIC and R^2 for the fitted model of mixed forests

Model	*Season*	*AIC*	*BIC*	*R^2c*	*R^2m*	*p-Value*
Model1	Spring	-542.6	-527.4	0.38	0.27	<.0001
	Summer	-608.2	-593.0	0.56	0.51	
	Fall	-615.7	-600.5	0.27	0.23	
	Winter	-444.7	-429.5	0.29	< 0.01	
	Year	-590.2	-575.0	0.31	0.24	
Model2	Spring	-541.5	-526.3	0.32	0.27	
	Summer	-607.7	-592.5	0.53	0.51	
	Fall	-617.3	-605.2	0.23	0.23	
	Winter	-444.2	-429.0	0.23	< 0.01	
	Year	-589.4	-574.2	0.24	0.24	
Model3	Spring	-542.6	-527.4	0.38	0.27	
	Summer	-608.2	-593.0	0.56	0.51	
	Fall	-615.7	-600.5	0.27	0.23	
	Winter	-444.7	-429.5	0.29	< 0.01	
	Year	-590.2	-575.0	0.31	0.24	
Model4	Spring	-541.5	-526.3	0.32	0.27	
	Summer	-607.7	-592.5	0.53	0.51	
	Fall	-617.3	-605.2	0.23	0.23	
	Winter	-444.2	-429.0	0.23	< 0.01	
	Year	-589.4	-574.2	0.24	0.24	

Table 4.2 showed that model1 provided lowest values in AIC and BIC and highest value in conditional R^2, which suggested that model1 fitted the data of softwood much better than other models. Analyses were then performed on the seasonal variations of R^2 values which exposed that the variance of spring NDVI was most explained by

combined effects of precipitation and temperature, while the variance of winter NDVI was least explained by models.

Table 4.3 revealed that in hardwood forests, the largest conditional R^2 value was derived from model1. The lowest AIC and BIC obtained from model1 suggested that model1 best fitted the data. In all seasons, conditional R^2 values obtained from all models were compared and it appeared that in hardwood forests the observed conditional R^2 value of spring was higher than values of other seasons. In spring, the largest conditional R^2 value which was derived from model1 amounts to 0.67.

Table 4.4 suggested that model1 provided the best fit of mixed forests data. The results showed that model1 had the highest conditional R^2, which implies that the variation of NDVI could be explained most by model1. Model1 was with the smallest AIC, and the smallest BIC, which implies that model1 is better than other models. In all seasons, the conditional R^2 value obtained from model1 was highest for the summer (0.56) and lowest for the fall (0.27).

A significant p-value (at 5% level of significance) in table2, table3 and table4 individually indicated that for each forest type, the fixed effects of meteorological variables significantly affects the seasonal and annual NDVIs.

Discussion

The goal of this research is to explore random and fixed effects on forest dynamics to meteorological factors. It was believed that the region-specific effect could be treated as a random effect in modeling (Lu and Zhang. 2012; Meng et al. 2007). Therefore, mixed-effects models containing different random coefficient configurations will be compared in a county scale. I fitted four types of LMMs for the purpose of comparison and selection of the best random structure for the fitted model. Firstly, to determine the optimal random effects structure for random intercept and random slope models, the model selection was performed based on AIC and BIC for determining whether to incorporate random effects from meteorological factors (precipitation, temperature or both) for a slope (or slopes) in a given model. AIC and BIC indicated that models without random effects from precipitation for a slope are equivalent to models with random effects from precipitation for a slope, which indicated that precipitation does not give rise to any random effects on fitted models. the AICs and BICs of two distinct types of resulting models: the random intercept model (model4) and the random intercept and random slope model (model1) were then compared. This comparison indicated that random intercept and random slope model is the most plausible one in terms of lower AIC and BIC values.

As a goodness of fit measure of models, I computed both the marginal and conditional R^2 values. To quantify the variance accounted by fixed effects, I employed R^2 to examine the random intercept model and the random intercept and slope model. The value of conditional R^2 derived from the random intercept and slope model was generally higher than the random intercept model indicating that the variance could be better explained by random-effects on both intercepts and slopes of models. This result has also been found by Meng et al (2007) that the LMM with both intercept and slope having random-effects best fits the data. This finding highlighted the random effects of temperature to explain forest dynamics in the Gulf Coast. Additionally, values of marginal R^2 were found lower than the corresponding conditional R^2, which was also found by Orelien and Edwards (2008) suggesting that the fixed-effects model was fitted less adequately than the mixed-effects model.

The importance of linear regression model in assessing relationship has been previously established, although most of the research has focused on the fixed-effects. The mixed-effects models incorporate spatial dependence in modeling the relationships between variables, and could consequently improve the estimates and reduced the bias which was present in the estimates of the fixed-effects models (Breidenbach et al, 2007; Meng et al. 2007; Zhang et al. 2008; Zhang et al. 2009). Mixed-effects models with forestry application were discussed by some scholars, most of which were conducted at the stand level (Galván et al. 2014; Breidenbach et al, 2007; Zhang et al. 2008; Zhang et al. 2005; Zhang and Borders. 2004; Hökkä 1997). An in-depth description of LMM application at the regional level is given for example by Meng et al (2007), which suggested that LMMs with random-effects on both intercepts and slopes best explained the variance of the surface area of NDVIs. In this study, it appeared that the largest R^2 value of model1 was 0.67 (spring) for the hardwood, 0.61 (spring) for the softwood, and 0.56 (summer) for the mixed forest, and suggested that in all three forest types, NDVI correlated quite differently with meteorological variables, with obvious temporal heterogeneity, which has also been observed in other regions (Chuai et al. 2013).

Conclusion

This study investigated the random-effects from four distinct types of linear mixed models. The performance of the model depended on random effect configurations. Indicators of model performance implies that the random-effects impact on both the intercept and slope in regression models, which is in accordance with Meng et al (2007).

The random intercept and random slope model fitted the data better (i.e., larger conditional R^2, smaller AIC, and smaller BIC) than other models, suggesting an improvement in model fitting by accounting for the combined effects of both fixed and random effects. This finding provided useful guidelines for choosing an appropriate model structure for using mixed linear model.

The use of LMM provides an important tool to link forest dynamics to meteorological variables. Given the advantage of a mixed-effects model that compared to a fixed-effects model, the mixed-effects model can be utilized to reduce the bias (Breidenbach et al, 2007). This study utilized LMM to explore forest dynamics that occurred in response to meteorological factors. The result displayed a presence of time-drift for the capability of the meteorological variables explaining forest dynamics. Actually, meteorological factors are observed to vary spatiotemporally and forest dynamics vary accordingly (Cruz-Cárdenas et al. 2016; Pacheco et al. 2010). The mixed-effects of temperature and fixed effect of precipitation were identified as main drivers for variations in forests. This research presented insights that can improve our understanding of forest dynamics to the changing climate in the Gulf Coast.

CHAPTER V

SUMMARY

The meteorological change was interpreted differently from the climate change in following three perspectives: firstly, according to the intergovernmental panel on climate change (IPCC) report (2014), climate change is defined as a change in the state of the climate that can be identified (e.g., by using statistical tests) by changes in the mean and/or the variability of its properties, and that persists for an extended period, typically decades or longer; while this study only focused on temperature/precipitation fluctuations in a one year period. Secondly, the framework convention on climate change (UNFCCC) makes defines climate change as a change of climate which is attributed directly or indirectly to human activity in addition to natural climate variability; while this study assumed the possible human disturbance as a constant effect to forest dynamics. Thirdly, this study placed focus on a general trend of meteorological variations not the changes in extreme weather and climate events.

The impact of the climate change induced meteorological fluctuations is important and was considered in many climate change studies. The forest dynamics needs consideration in such studies, especially in Gulf of Mexico coastal region. However, the effect of changes in meteorological factors on forest dynamics was mostly discussed at a stand scale, while at a landscape scale is rarely quantified in studies. Understanding relationships between meteorological factors and forest dynamics is vital for addressing a wide range of contemporary environmental issues such as biodiversity loss, deforestation, land/soil degradation, and climate change. I explored forest dynamics to spatiotemporal changes of temperature and precipitation across the GOM coastal region and obtained a comprehensive understanding about its spatiotemporal properties of each major forest type.

In this study, the contributions of changes in meteorological parameters to forest dynamics were analyzed and quantified. The spatiotemporal heterogeneity in the response of forests to meteorological change was observed to exist in the GOM coastal region. From a temporal aspect, statistical regression modeling based approaches were used for comparing forest dynamics to meteorological changes of different seasons. Models were always characterized by better performances in spring and summer. From a spatial aspect, the complexity of forest types need to be considered when modeling forest dynamics. Forest community consists of numerous types, each of which has its own spatial and temporal signature. Therefore, to better understand how meteorological changes influence forest dynamics, this study also compared the differences between forest dynamics of different forest types and it showed that forest type results in distinct response to explanatory variables (e.g., precipitation, temperature and soil texture).

Statistical regression methods provide a variety of possible means for finding the best fitted model in order to explore forest dynamics to meteorological changes. In this context, the development, assessment and selection of models have a great potential to study on, which was considered in this study. The fixed-effects method (e.g., OLS and GWR) have been proved to be an adequate tool to model relationships. However, spatial relationships often involve spatial dependence, with correlations exist between the values of a random variable at a location and the values of the same variable at neighbors. This is caused by underlying spatial processes that give rise to a localized covariation among variables, and, consequently, clusters of similar or dissimilar values of the variables (Zhang et al. 2009). In order to avoid the estimation bias inherent in non-spatial models (e.g., OLS) and to consider spatial processes, GWR models were utilized and compared with OLS models. It was found that GWR models are better than global regression OLS models, which is in accordance with several other studies (Zhao et al., 2010; Gao et al., 2012; Su et al., 2012; Zhao et al., 2014).

Since results of this study indicate an explanatory power of models with explanatory variables (e.g., precipitation, temperature and soil texture) explaining forest dynamics, I conclude that the forest dynamics depends on the impact of changes in meteorological factors and soil texture in the Gulf of Mexico coastal region. In other regions, there might be other relationships, but especially with similar climatic conditions, the impact of meteorological factors or soil on forest dynamics is expected to be of a similar magnitude. This may indicate the importance of the results of this research revealing the important role of meteorological factors and soil texture. Therefore, further forest dynamics in GOM coastal region can be predicted by meteorological factor and soil texture.

I have fitted fixed-effects and mixed-effects models to describe the forest dynamics to meteorological changes in GOM coastal region. There are still numbers of regression methods exist for determining spatial relationships. In future studies, more methods could be carried out to identify which model would best fit the data and have the strongest explanatory power. Moreover, it was believed that forest dynamics was determined by resource-based factors such as radiation, nutrients supply, topography and drainage, and disturbance-based factors such as soil acidity, fire and air pollution (Murphy and Bowman 2012; Pretzsch 2009). The variance of the model must be further analyzed in order to identify the importance of other potential explanatory variables. Additionally, the time-series data have been proved to have a great potential to capture fluctuations of climate and forest dynamics in many studies (Li et al. 2013; Neeti et al. 2012; de Jong et al. 2011; Höpfner and Scherer. 2011; Verbesselt et al. 2010; Powell et al. 2010; Omuto et al. 2010; McCloy and Lucht. 2004). Therefore, I will include data of many more years in future studies.

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APPENDIX A

DATA TABLES

Table A.1 MODIS NDVI (MOD13Q1) from March (2012) to February (2013)

	File Name	*Acquisition Date*
1	MOD13Q1.A2013049.h11v06.005.2013067184209.hdf	2013/2/18
2	MOD13Q1.A2013049.h09v06.005.2013067182827.hdf	2013/2/18
3	MOD13Q1.A2013049.h11v05.005.2013067205911.hdf	2013/2/18
4	MOD13Q1.A2013049.h10v05.005.2013067190714.hdf	2013/2/18
5	MOD13Q1.A2013049.h09v05.005.2013067192706.hdf	2013/2/18
6	MOD13Q1.A2013049.h10v06.005.2013067173711.hdf	2013/2/18
7	MOD13Q1.A2013033.h10v05.005.2013051105127.hdf	2013/2/2
8	MOD13Q1.A2013033.h11v06.005.2013051095411.hdf	2013/2/2
9	MOD13Q1.A2013033.h09v05.005.2013051105915.hdf	2013/2/2
10	MOD13Q1.A2013033.h11v05.005.2013051102500.hdf	2013/2/2
11	MOD13Q1.A2013033.h10v06.005.2013051103057.hdf	2013/2/2
12	MOD13Q1.A2013033.h09v06.005.2013051102946.hdf	2013/2/2
13	MOD13Q1.A2013017.h10v05.005.2013039190155.hdf	2013/1/17
14	MOD13Q1.A2013017.h11v05.005.2013039211440.hdf	2013/1/17
15	MOD13Q1.A2013017.h10v06.005.2013042063745.hdf	2013/1/17
16	MOD13Q1.A2013017.h09v06.005.2013039193536.hdf	2013/1/17
17	MOD13Q1.A2013017.h11v06.005.2013039205306.hdf	2013/1/17
18	MOD13Q1.A2013017.h09v05.005.2013039213645.hdf	2013/1/17
19	MOD13Q1.A2013001.h11v06.005.2013018040941.hdf	2013/1/1
20	MOD13Q1.A2013001.h10v05.005.2013018041412.hdf	2013/1/1
21	MOD13Q1.A2013001.h09v06.005.2013018015806.hdf	2013/1/1
22	MOD13Q1.A2013001.h09v05.005.2013018035349.hdf	2013/1/1
23	MOD13Q1.A2013001.h11v05.005.2013018034942.hdf	2013/1/1
24	MOD13Q1.A2013001.h10v06.005.2013018035929.hdf	2013/1/1
25	MOD13Q1.A2012353.h11v05.005.2013009145647.hdf	2012/12/18
26	MOD13Q1.A2012353.h10v06.005.2013009145928.hdf	2012/12/18
27	MOD13Q1.A2012353.h10v05.005.2013009152629.hdf	2012/12/18
28	MOD13Q1.A2012353.h09v05.005.2013009150640.hdf	2012/12/18
29	MOD13Q1.A2012353.h09v06.005.2013009144953.hdf	2012/12/18
30	MOD13Q1.A2012353.h11v06.005.2013009152242.hdf	2012/12/18
31	MOD13Q1.A2012337.h10v06.005.2012355094444.hdf	2012/12/2
32	MOD13Q1.A2012337.h11v05.005.2012355102736.hdf	2012/12/2
33	MOD13Q1.A2012337.h09v06.005.2012355102110.hdf	2012/12/2
34	MOD13Q1.A2012337.h10v05.005.2012355095743.hdf	2012/12/2
35	MOD13Q1.A2012337.h09v05.005.2012355103424.hdf	2012/12/2
36	MOD13Q1.A2012337.h11v06.005.2012355100616.hdf	2012/12/2
37	MOD13Q1.A2012321.h11v06.005.2012339011955.hdf	2012/11/16

Table A.1 (Continued)

38	MOD13Q1.A2012321.h09v06.005.2012339025804.hdf	2012/11/16
39	MOD13Q1.A2012321.h10v06.005.2012339025709.hdf	2012/11/16
40	MOD13Q1.A2012321.h09v05.005.2012339031137.hdf	2012/11/16
41	MOD13Q1.A2012321.h10v05.005.2012339030953.hdf	2012/11/16
42	MOD13Q1.A2012321.h11v05.005.2012339030726.hdf	2012/11/16
43	MOD13Q1.A2012305.h10v06.005.201232203311З.hdf	2012/10/31
44	MOD13Q1.A2012305.h11v05.005.2012322042608.hdf	2012/10/31
45	MOD13Q1.A2012305.h10v05.005.2012322042823.hdf	2012/10/31
46	MOD13Q1.A2012305.h09v06.005.2012322042117.hdf	2012/10/31
47	MOD13Q1.A2012305.h09v05.005.2012322042054.hdf	2012/10/31
48	MOD13Q1.A2012305.h11v06.005.2012322050522.hdf	2012/10/31
49	MOD13Q1.A2012289.h10v05.005.2012311101834.hdf	2012/10/15
50	MOD13Q1.A2012289.h09v05.005.2012311101002.hdf	2012/10/15
51	MOD13Q1.A2012289.h10v06.005.2012311095925.hdf	2012/10/15
52	MOD13Q1.A2012289.h09v06.005.2012311095606.hdf	2012/10/15
53	MOD13Q1.A2012289.h11v06.005.2012311103424.hdf	2012/10/15
54	MOD13Q1.A2012289.h11v05.005.2012311100624.hdf	2012/10/15
55	MOD13Q1.A2012273.h11v06.005.2012299101346.hdf	2012/9/29
56	MOD13Q1.A2012273.h09v05.005.2012299103301.hdf	2012/9/29
57	MOD13Q1.A2012273.h10v06.005.2012299101827.hdf	2012/9/29
58	MOD13Q1.A2012273.h10v05.005.2012299104545.hdf	2012/9/29
59	MOD13Q1.A2012273.h11v05.005.2012299102523.hdf	2012/9/29
60	MOD13Q1.A2012273.h09v06.005.2012299101746.hdf	2012/9/29
61	MOD13Q1.A2012257.h09v05.005.2012275110740.hdf	2012/9/13
62	MOD13Q1.A2012257.h10v06.005.2012275105013.hdf	2012/9/13
63	MOD13Q1.A2012257.h11v05.005.2012275105939.hdf	2012/9/13
64	MOD13Q1.A2012257.h10v05.005.2012275111116.hdf	2012/9/13
65	MOD13Q1.A2012257.h09v06.005.2012275105037.hdf	2012/9/13
66	MOD13Q1.A2012257.h11v06.005.2012275103928.hdf	2012/9/13
67	MOD13Q1.A2012241.h11v06.005.2012258030419.hdf	2012/8/28
68	MOD13Q1.A2012241.h10v05.005.2012258035120.hdf	2012/8/28
69	MOD13Q1.A2012241.h09v06.005.2012258030806.hdf	2012/8/28
70	MOD13Q1.A2012241.h09v05.005.2012258031758.hdf	2012/8/28
71	MOD13Q1.A2012241.h11v05.005.2012258032539.hdf	2012/8/28
72	MOD13Q1.A2012241.h10v06.005.2012258030636.hdf	2012/8/28
73	MOD13Q1.A2012225.h10v05.005.2012242064616.hdf	2012/8/12
74	MOD13Q1.A2012225.h09v05.005.2012242060651.hdf	2012/8/12
75	MOD13Q1.A2012225.h09v06.005.2012242055028.hdf	2012/8/12
76	MOD13Q1.A2012225.h11v06.005.2012242065341.hdf	2012/8/12

Table A.1 (Continued)

77	MOD13Q1.A2012225.h10v06.005.2012242054010.hdf	2012/8/12
78	MOD13Q1.A2012225.h11v05.005.2012242070320.hdf	2012/8/12
79	MOD13Q1.A2012209.h11v06.005.2012228192404.hdf	2012/7/27
80	MOD13Q1.A2012209.h11v05.005.2012228194514.hdf	2012/7/27
81	MOD13Q1.A2012209.h10v05.005.2012228190929.hdf	2012/7/27
82	MOD13Q1.A2012209.h09v05.005.2012228190117.hdf	2012/7/27
83	MOD13Q1.A2012209.h10v06.005.2012228185311.hdf	2012/7/27
84	MOD13Q1.A2012209.h09v06.005.2012228190101.hdf	2012/7/27
85	MOD13Q1.A2012193.h09v05.005.2012212123942.hdf	2012/7/11
86	MOD13Q1.A2012193.h10v06.005.2012212120453.hdf	2012/7/11
87	MOD13Q1.A2012193.h11v05.005.2012212121120.hdf	2012/7/11
88	MOD13Q1.A2012193.h10v05.005.2012212122053.hdf	2012/7/11
89	MOD13Q1.A2012193.h09v06.005.2012212120335.hdf	2012/7/11
90	MOD13Q1.A2012193.h11v06.005.2012212121055.hdf	2012/7/11
91	MOD13Q1.A2012177.h11v06.005.2012209003614.hdf	2012/6/25
92	MOD13Q1.A2012177.h09v06.005.2012209005357.hdf	2012/6/25
93	MOD13Q1.A2012177.h10v06.005.2012209011146.hdf	2012/6/25
94	MOD13Q1.A2012177.h09v05.005.2012209010459.hdf	2012/6/25
95	MOD13Q1.A2012177.h10v05.005.2012209004358.hdf	2012/6/25
96	MOD13Q1.A2012177.h11v05.005.2012209010343.hdf	2012/6/25
97	MOD13Q1.A2012161.h09v06.005.2012178054835.hdf	2012/6/9
98	MOD13Q1.A2012161.h11v06.005.2012178052425.hdf	2012/6/9
99	MOD13Q1.A2012161.h11v05.005.2012178060853.hdf	2012/6/9
100	MOD13Q1.A2012161.h09v05.005.2012178060930.hdf	2012/6/9
101	MOD13Q1.A2012161.h10v05.005.2012178055956.hdf	2012/6/9
102	MOD13Q1.A2012161.h10v06.005.2012178054214.hdf	2012/6/9
103	MOD13Q1.A2012145.h10v06.005.2012166112539.hdf	2012/5/24
104	MOD13Q1.A2012145.h11v06.005.2012166104819.hdf	2012/5/24
105	MOD13Q1.A2012145.h09v06.005.2012166105111.hdf	2012/5/24
106	MOD13Q1.A2012145.h10v05.005.2012166112540.hdf	2012/5/24
107	MOD13Q1.A2012145.h09v05.005.2012166111623.hdf	2012/5/24
108	MOD13Q1.A2012145.h11v05.005.2012166111707.hdf	2012/5/24
109	MOD13Q1.A2012129.h11v05.005.2012146111034.hdf	2012/5/8
110	MOD13Q1.A2012129.h09v06.005.2012146112301.hdf	2012/5/8
111	MOD13Q1.A2012129.h10v06.005.2012146122535.hdf	2012/5/8
112	MOD13Q1.A2012129.h11v06.005.2012146111906.hdf	2012/5/8
113	MOD13Q1.A2012129.h10v05.005.2012146113451.hdf	2012/5/8
114	MOD13Q1.A2012129.h09v05.005.2012146110302.hdf	2012/5/8
115	MOD13Q1.A2012113.h09v05.005.2012130034738.hdf	2012/4/22

Table A.1 (Continued)

116	MOD13Q1.A2012113.h10v06.005.2012130033204.hdf	2012/4/22
117	MOD13Q1.A2012113.h09v06.005.2012130030636.hdf	2012/4/22
118	MOD13Q1.A2012113.h11v06.005.2012130033729.hdf	2012/4/22
119	MOD13Q1.A2012113.h10v05.005.2012130044938.hdf	2012/4/22
120	MOD13Q1.A2012113.h11v05.005.2012130031329.hdf	2012/4/22
121	MOD13Q1.A2012097.h11v05.005.2012114123208.hdf	2012/4/6
122	MOD13Q1.A2012097.h09v05.005.2012114114524.hdf	2012/4/6
123	MOD13Q1.A2012097.h10v05.005.2012114114223.hdf	2012/4/6
124	MOD13Q1.A2012097.h10v06.005.2012114110338.hdf	2012/4/6
125	MOD13Q1.A2012097.h09v06.005.2012114111649.hdf	2012/4/6
126	MOD13Q1.A2012097.h11v06.005.2012114113315.hdf	2012/4/6
127	MOD13Q1.A2012081.h11v05.005.2012107202420.hdf	2012/3/21
128	MOD13Q1.A2012081.h10v06.005.2012107195131.hdf	2012/3/21
129	MOD13Q1.A2012081.h11v06.005.2012107201758.hdf	2012/3/21
130	MOD13Q1.A2012081.h10v05.005.2012107201259.hdf	2012/3/21
131	MOD13Q1.A2012081.h09v05.005.2012107200459.hdf	2012/3/21
132	MOD13Q1.A2012081.h09v06.005.2012107200414.hdf	2012/3/21
133	MOD13Q1.A2012065.h09v06.005.2012082114844.hdf	2012/3/5
134	MOD13Q1.A2012065.h11v06.005.2012082113628.hdf	2012/3/5
135	MOD13Q1.A2012065.h10v05.005.2012082115842.hdf	2012/3/5
136	MOD13Q1.A2012065.h09v05.005.2012082115239.hdf	2012/3/5
137	MOD13Q1.A2012065.h11v05.005.2012082120948.hdf	2012/3/5
138	MOD13Q1.A2012065.h10v06.005.2012082113904.hdf	2012/3/5

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Table A.2 MODIS NDVI (MOD13Q1) from March (2009) to February (2010)

	Local Granule ID	*Acquisition Date*
1	MOD13Q1.A2010049.h09v05.005.2010067030234.hdf	2010/2/18
2	MOD13Q1.A2010049.h09v06.005.2010066235649.hdf	2010/2/18
3	MOD13Q1.A2010049.h11v05.005.2010066164249.hdf	2010/2/18
4	MOD13Q1.A2010049.h10v06.005.2010067103334.hdf	2010/2/18
5	MOD13Q1.A2010049.h11v06.005.2010066144528.hdf	2010/2/18
6	MOD13Q1.A2010049.h10v05.005.2010067114503.hdf	2010/2/18
7	MOD13Q1.A2010033.h09v05.005.2010051210854.hdf	2010/2/2
8	MOD13Q1.A2010033.h09v06.005.2010050205231.hdf	2010/2/2
9	MOD13Q1.A2010033.h11v05.005.2010050124638.hdf	2010/2/2
10	MOD13Q1.A2010033.h10v06.005.2010051020620.hdf	2010/2/2
11	MOD13Q1.A2010033.h11v06.005.2010051152221.hdf	2010/2/2
12	MOD13Q1.A2010033.h10v05.005.2010051080246.hdf	2010/2/2
13	MOD13Q1.A2010017.h11v06.005.2010035144503.hdf	2010/1/17
14	MOD13Q1.A2010017.h11v05.005.2010035154043.hdf	2010/1/17
15	MOD13Q1.A2010017.h10v06.005.2010036141005.hdf	2010/1/17
16	MOD13Q1.A2010017.h09v06.005.2010035211358.hdf	2010/1/17
17	MOD13Q1.A2010017.h09v05.005.2010036011343.hdf	2010/1/17
18	MOD13Q1.A2010017.h10v05.005.2010036162319.hdf	2010/1/17
19	MOD13Q1.A2010001.h09v06.005.2010027024403.hdf	2010/1/1
20	MOD13Q1.A2010001.h10v06.005.2010028005043.hdf	2010/1/1
21	MOD13Q1.A2010001.h10v05.005.2010028005522.hdf	2010/1/1
22	MOD13Q1.A2010001.h11v05.005.2010026183306.hdf	2010/1/1
23	MOD13Q1.A2010001.h09v05.005.2010027084109.hdf	2010/1/1
24	MOD13Q1.A2010001.h11v06.005.2010026161740.hdf	2010/1/1
25	MOD13Q1.A2009353.h11v05.005.2010008003036.hdf	2009/12/19
26	MOD13Q1.A2009353.h10v05.005.2010009082500.hdf	2009/12/19
27	MOD13Q1.A2009353.h09v05.005.2010008125955.hdf	2009/12/19
28	MOD13Q1.A2009353.h11v06.005.2010007193134.hdf	2009/12/19
29	MOD13Q1.A2009353.h10v06.005.2010009072815.hdf	2009/12/19
30	MOD13Q1.A2009353.h09v06.005.2010008051705.hdf	2009/12/19
31	MOD13Q1.A2009337.h11v05.005.2009354214722.hdf	2009/12/3
32	MOD13Q1.A2009337.h10v05.005.2009355133326.hdf	2009/12/3
33	MOD13Q1.A2009337.h09v06.005.2009355010142.hdf	2009/12/3
34	MOD13Q1.A2009337.h10v06.005.2009355125317.hdf	2009/12/3
35	MOD13Q1.A2009337.h11v06.005.2009354200828.hdf	2009/12/3
36	MOD13Q1.A2009337.h09v05.005.2009355043100.hdf	2009/12/3
37	MOD13Q1.A2009321.h09v05.005.2009338234505.hdf	2009/11/17

Table A.2 (Continued)

38	MOD13Q1.A2009321.h11v05.005.2009338075005.hdf	2009/11/17
39	MOD13Q1.A2009321.h10v06.005.2009338185040.hdf	2009/11/17
40	MOD13Q1.A2009321.h11v06.005.2009338150446.hdf	2009/11/17
41	MOD13Q1.A2009321.h10v05.005.2009338195219.hdf	2009/11/17
42	MOD13Q1.A2009321.h09v06.005.2009338143058.hdf	2009/11/17
43	MOD13Q1.A2009305.h09v06.005.2009322170839.hdf	2009/11/1
44	MOD13Q1.A2009305.h10v06.005.2009323052858.hdf	2009/11/1
45	MOD13Q1.A2009305.h11v06.005.2009322090953.hdf	2009/11/1
46	MOD13Q1.A2009305.h10v05.005.2009323053434.hdf	2009/11/1
47	MOD13Q1.A2009305.h11v05.005.2009322114038.hdf	2009/11/1
48	MOD13Q1.A2009305.h09v05.005.2009322223228.hdf	2009/11/1
49	MOD13Q1.A2009289.h11v05.005.2009307202207.hdf	2009/10/16
50	MOD13Q1.A2009289.h09v05.005.2009308060933.hdf	2009/10/16
51	MOD13Q1.A2009289.h09v06.005.2009308011036.hdf	2009/10/16
52	MOD13Q1.A2009289.h10v06.005.2009309044017.hdf	2009/10/16
53	MOD13Q1.A2009289.h11v06.005.2009307183458.hdf	2009/10/16
54	MOD13Q1.A2009289.h10v05.005.2009309073752.hdf	2009/10/16
55	MOD13Q1.A2009273.h11v05.005.2009305230701.hdf	2009/9/30
56	MOD13Q1.A2009273.h09v05.005.2009306035621.hdf	2009/9/30
57	MOD13Q1.A2009273.h11v06.005.2009305182827.hdf	2009/9/30
58	MOD13Q1.A2009273.h10v05.005.2009306035641.hdf	2009/9/30
59	MOD13Q1.A2009273.h10v06.005.2009306001642.hdf	2009/9/30
60	MOD13Q1.A2009273.h09v06.005.2009305201055.hdf	2009/9/30
61	MOD13Q1.A2009257.h09v06.005.2009275220252.hdf	2009/9/14
62	MOD13Q1.A2009257.h10v06.005.2009275181021.hdf	2009/9/14
63	MOD13Q1.A2009257.h11v06.005.2009275195032.hdf	2009/9/14
64	MOD13Q1.A2009257.h09v05.005.2009276010739.hdf	2009/9/14
65	MOD13Q1.A2009257.h11v05.005.2009275202401.hdf	2009/9/14
66	MOD13Q1.A2009257.h10v05.005.2009276034808.hdf	2009/9/14
67	MOD13Q1.A2009241.h09v06.005.2009258230105.hdf	2009/8/29
68	MOD13Q1.A2009241.h10v06.005.2009260060304.hdf	2009/8/29
69	MOD13Q1.A2009241.h09v05.005.2009259044004.hdf	2009/8/29
70	MOD13Q1.A2009241.h11v06.005.2009258154454.hdf	2009/8/29
71	MOD13Q1.A2009241.h11v05.005.2009258180706.hdf	2009/8/29
72	MOD13Q1.A2009241.h10v05.005.2009260071119.hdf	2009/8/29
73	MOD13Q1.A2009225.h10v06.005.2009247052408.hdf	2009/8/13
74	MOD13Q1.A2009225.h11v06.005.2009246225136.hdf	2009/8/13
75	MOD13Q1.A2009225.h09v06.005.2009247064757.hdf	2009/8/13
76	MOD13Q1.A2009225.h10v05.005.2009247064436.hdf	2009/8/13

Table A.2 (Continued)

77	MOD13Q1.A2009225.h11v05.005.2009246231034.hdf	2009/8/13
78	MOD13Q1.A2009225.h09v05.005.2009247133101.hdf	2009/8/13
79	MOD13Q1.A2009209.h11v05.005.2009227205201.hdf	2009/7/28
80	MOD13Q1.A2009209.h09v05.005.2009228063939.hdf	2009/7/28
81	MOD13Q1.A2009209.h10v06.005.2009229000818.hdf	2009/7/28
82	MOD13Q1.A2009209.h11v06.005.2009227185342.hdf	2009/7/28
83	MOD13Q1.A2009209.h09v06.005.2009228020411.hdf	2009/7/28
84	MOD13Q1.A2009209.h10v05.005.2009229014338.hdf	2009/7/28
85	MOD13Q1.A2009193.h09v06.005.2009212015754.hdf	2009/7/12
86	MOD13Q1.A2009193.h10v06.005.2009213133041.hdf	2009/7/12
87	MOD13Q1.A2009193.h09v05.005.2009212090048.hdf	2009/7/12
88	MOD13Q1.A2009193.h10v05.005.2009213150306.hdf	2009/7/12
89	MOD13Q1.A2009193.h11v06.005.2009211111919.hdf	2009/7/12
90	MOD13Q1.A2009193.h11v05.005.2009211175229.hdf	2009/7/12
91	MOD13Q1.A2009177.h09v06.005.2009200003450.hdf	2009/6/26
92	MOD13Q1.A2009177.h09v05.005.2009199001950.hdf	2009/6/26
93	MOD13Q1.A2009177.h10v06.005.2009200010646.hdf	2009/6/26
94	MOD13Q1.A2009177.h11v06.005.2009200023721.hdf	2009/6/26
95	MOD13Q1.A2009177.h10v05.005.2009199045936.hdf	2009/6/26
96	MOD13Q1.A2009177.h11v05.005.2009200014029.hdf	2009/6/26
97	MOD13Q1.A2009161.h10v06.005.2009182221157.hdf	2009/6/10
98	MOD13Q1.A2009161.h11v06.005.2009180035307.hdf	2009/6/10
99	MOD13Q1.A2009161.h09v06.005.2009180163448.hdf	2009/6/10
100	MOD13Q1.A2009161.h10v05.005.2009182213448.hdf	2009/6/10
101	MOD13Q1.A2009161.h11v05.005.2009180053250.hdf	2009/6/10
102	MOD13Q1.A2009161.h09v05.005.2009181033925.hdf	2009/6/10
103	MOD13Q1.A2009145.h09v05.005.2009166085552.hdf	2009/5/25
104	MOD13Q1.A2009145.h10v06.005.2009167024506.hdf	2009/5/25
105	MOD13Q1.A2009145.h11v06.005.2009166025634.hdf	2009/5/25
106	MOD13Q1.A2009145.h09v06.005.2009166133311.hdf	2009/5/25
107	MOD13Q1.A2009145.h10v05.005.2009167045340.hdf	2009/5/25
108	MOD13Q1.A2009145.h11v05.005.2009165083926.hdf	2009/5/25
109	MOD13Q1.A2009129.h09v06.005.2009149020130.hdf	2009/5/9
110	MOD13Q1.A2009129.h09v05.005.2009150034509.hdf	2009/5/9
111	MOD13Q1.A2009129.h11v06.005.2009147143028.hdf	2009/5/9
112	MOD13Q1.A2009129.h10v05.005.2009150190726.hdf	2009/5/9
113	MOD13Q1.A2009129.h10v06.005.2009150154651.hdf	2009/5/9
114	MOD13Q1.A2009129.h11v05.005.2009147182845.hdf	2009/5/9
115	MOD13Q1.A2009113.h09v06.005.2009130193659.hdf	2009/4/23

Table A.2 (Continued)

116	MOD13Q1.A2009113.h11v05.005.2009130213223.hdf	2009/4/23
117	MOD13Q1.A2009113.h11v06.005.2009130161938.hdf	2009/4/23
118	MOD13Q1.A2009113.h09v05.005.2009130203731.hdf	2009/4/23
119	MOD13Q1.A2009113.h10v06.005.2009131181650.hdf	2009/4/23
120	MOD13Q1.A2009113.h10v05.005.2009132042906.hdf	2009/4/23
121	MOD13Q1.A2009097.h11v06.005.2009123092929.hdf	2009/4/7
122	MOD13Q1.A2009097.h10v06.005.2009125072214.hdf	2009/4/7
123	MOD13Q1.A2009097.h09v06.005.2009124012925.hdf	2009/4/7
124	MOD13Q1.A2009097.h09v05.005.2009124093050.hdf	2009/4/7
125	MOD13Q1.A2009097.h11v05.005.2009123112209.hdf	2009/4/7
126	MOD13Q1.A2009097.h10v05.005.2009125092335.hdf	2009/4/7
127	MOD13Q1.A2009081.h09v05.005.2009100062020.hdf	2009/3/22
128	MOD13Q1.A2009081.h10v06.005.2009101000031.hdf	2009/3/22
129	MOD13Q1.A2009081.h11v06.005.2009099112007.hdf	2009/3/22
130	MOD13Q1.A2009081.h09v06.005.2009100004033.hdf	2009/3/22
131	MOD13Q1.A2009081.h10v05.005.2009101013426.hdf	2009/3/22
132	MOD13Q1.A2009081.h11v05.005.2009099135353.hdf	2009/3/22
133	MOD13Q1.A2009065.h10v06.005.2009086073611.hdf	2009/3/6
134	MOD13Q1.A2009065.h09v05.005.2009083231847.hdf	2009/3/6
135	MOD13Q1.A2009065.h11v06.005.2009082230105.hdf	2009/3/6
136	MOD13Q1.A2009065.h10v05.005.2009086094929.hdf	2009/3/6
137	MOD13Q1.A2009065.h09v06.005.2009083132938.hdf	2009/3/6
138	MOD13Q1.A2009065.h11v05.005.2009083002209.hdf	2009/3/6

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Table A.3 Monthly and annual precipitation (from the year of 2002 to 2016)

	Year	*File Name*
1	2002	PRISM_ppt_stable_4kmM3_2002_all_bil.zip
2	2003	PRISM_ppt_stable_4kmM3_2003_all_bil.zip
3	2004	PRISM_ppt_stable_4kmM3_2004_all_bil.zip
4	2005	PRISM_ppt_stable_4kmM3_2005_all_bil.zip
5	2006	PRISM_ppt_stable_4kmM3_2006_all_bil.zip
6	2007	PRISM_ppt_stable_4kmM3_2007_all_bil.zip
7	2008	PRISM_ppt_stable_4kmM3_2008_all_bil.zip
8	2009	PRISM_ppt_stable_4kmM3_2009_all_bil.zip
9	2010	PRISM_ppt_stable_4kmM3_2010_all_bil.zip
10	2011	PRISM_ppt_stable_4kmM3_2011_all_bil.zip
11	2012	PRISM_ppt_stable_4kmM3_2012_all_bil.zip
12	2013	PRISM_ppt_stable_4kmM3_2013_all_bil.zip
13	2014	PRISM_ppt_stable_4kmM3_2014_all_bil.zip
14	2015	PRISM_ppt_stable_4kmM3_2015_all_bil.zip
15	2016	PRISM_ppt_stable_4kmM3_2016_all_bil.zip

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Table A.4 Monthly and annual mean temperature (from the year of 2002 to 2016)

	Year	*File Name*
1	2002	PRISM_tmean_stable_4kmM2_2002_all_bil
2	2003	PRISM_tmean_stable_4kmM2_2003_all_bil
3	2004	PRISM_tmean_stable_4kmM2_2004_all_bil
4	2005	PRISM_tmean_stable_4kmM2_2005_all_bil
5	2006	PRISM_tmean_stable_4kmM2_2006_all_bil
6	2007	PRISM_tmean_stable_4kmM2_2007_all_bil
7	2008	PRISM_tmean_stable_4kmM2_2008_all_bil
8	2009	PRISM_tmean_stable_4kmM2_2009_all_bil
9	2010	PRISM_tmean_stable_4kmM2_2010_all_bil
10	2011	PRISM_tmean_stable_4kmM2_2011_all_bil
11	2012	PRISM_tmean_stable_4kmM2_2012_all_bil
12	2013	PRISM_tmean_stable_4kmM2_2013_all_bil
13	2014	PRISM_tmean_stable_4kmM2_2014_all_bil
14	2015	PRISM_tmean_stable_4kmM2_2015_all_bil
15	2016	PRISM_tmean_stable_4kmM2_2016_all_bil

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Table A.5 Gridded Soil Survey Geographic (gSSURGO) by State

	State	*File Name*
1	Alabama	soils_GSSURGO_al_3319029_01.zip
2	Florida	soils_GSSURGO_fl_3316703_01.zip
3	Georgia	soils_GSSURGO_ga_3325011_01.zip
4	Louisiana	soils_GSSURGO_la_3320215_01.zip
5	Mississippi	soils_GSSURGO_ms_2585009_02.zip
6	Texas	soils_GSSURGO_tx_3325007_01.zip

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