Application of Random Effects to Explore the Gulf of Mexico Coastal Forest Dynamics in Relation to Meteorological Factors

Tianyu Li, Qingmin Meng, and Qian Du, *Fellow, IEEE*

***Abstract*—The forest dynamics are usually explained by the precipitation and temperature through fixed effects models using ordinary least squares and geographically weighted regression methods. However, forest dynamics were found insufficiently explained by meteorological factors as the fixed effects models were not designed to account for random effects. In this study, we utilized three types of forests located in the Gulf of Mexico Coast region, including softwood, hardwood, and mixed forests to investigate the underlying forest dynamics to meteorological variations by incorporating random effects into fixed effects models. Four types of linear mixed effects models (LMMs) were developed for regressing the normalized difference of vegetation index (NDVI) against two explanatory variables: precipitation and temperature. By assuming that the intercept and slope parameters estimated from LMMs would vary randomly, we intended to explore if the amount of variation in the NDVI variables could be reduced by the use of random effects variables. The results suggested that the random intercept and random slope model fitted the data better than the random intercept model with higher R^2, lower Akaike information criterion, and Bayesian information criterion values. The R^2 value indicated that the explanatory power of the LMM varies between forest types. Moreover, this study revealed that a linear mixed effects model could significantly reduce the unexplained variance by introducing random effects variables, and forest dynamics is a synthetic result of the mixed effects of temperature and fixed effects of precipitation.**

***Index Terms*—Forest dynamics, linear mixed effects model (LMM), precipitation, temperature.**

I. Introduction

Climate change is of the fundamental importance to the changes in vegetation conditions [1]. Climatology has a specific role in explaining vegetation phenological changes [2]. It has been demonstrated that the worldwide changes in the functional diversity in forests are measurable and predictable [3]. For instance, the distribution of vegetation can be explained by climatic factors, such as precipitation, temperature, potential evapotranspiration, water surplus, and water deficit [4]. Changes in the precipitation and temperature patterns were found related to the spatial vegetation distribution [5]–[7]. As previous studies have noted, factors, such as precipitation and temperature, could alter vegetation patterns, and which were believed capable of explaining the climate-related variation in forests [8]. Some regions are affected primarily by a single climatic factor: either temperature or precipitation. For instance, Wang *et al*. [9] suggested that the vegetation growth in North America's mid to high latitudes is very sensitive to the temperature changes and can be partly explained by changes in the trends of temperatures. Karnieli *et al*. [10] also demonstrated that temperature could be applied to explain vegetation changes over the North American continent and have found that the normalized difference of vegetation index (NDVI) and temperature relationship varies with location, season, and vegetation type. Moreover, the trend and magnitude of the NDVI values for most forests were found correlated with the spatiotemporal variability of precipitation in North America's low latitude [5]. Some climate change-induced alterations to forests were compounded simultaneously by the temperature and precipitation. For instance, the distribution and structure of the Gulf of Mexico (GOM) mangroves forests were found significantly influenced by both precipitation and temperature [11]. Li and Meng [12] have examined the effects of climate change on forest dynamics across the Gulf Coast of the United States and found that the seasonality of precipitation and temperature can explain forest dynamics.

NDVI is a commonly used greenness indicator, which indicates the presence, amount, and vigor of green vegetation [2], [5], [13]–[15]. Vegetation activities and dynamics can be quantified by NDVI at a landscape [16], [17], regional [16], [18], [19], [20], and global scale [10], [21]. NDVI has been used to parameterize the models relating to phenology for ecological, climatic, and agricultural applications [2], [16]. Additionally, NDVI has also been utilized to indicate spatiotemporal forest dynamics under climate change conditions [12]. For addressing the spatial controls of changes in the vegetation, researchers attempted to use the climate-NDVI data relationship. Liu *et al.* [22] show that the spatial heterogeneity of the climate-NDVI relationship is driven by vegetation type and climate conditions. Moreover, the climate–NDVI relationship also exhibits seasonal variations [23]. For instance, Gómez-Mendoza *et al.* [5] have found that phenological changes in NDVI are related to the annual and seasonal cycles of temperature and precipitation. It

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was believed that the implication of the spatiotemporal dynamics of climate-NDVI relationships is valuable for the understanding of land surface ecosystems and environmental management [7], [23].

Usually, linear regression models were developed and utilized to quantify relationships between forest dynamics and meteorological factors. Much of these research attempts to explore the climate-related changing patterns of forests by using fixed effects approaches, such as ordinary least squares (OLS) and geographically weighted regression (GWR). However, the classic linear regression, such as OLS, is not suitable for analyzing spatially correlated observations and measurements [24]. The GWR is a local modeling technique to estimate model coefficients with spatially varying relationships and spatial autocorrelation of model residuals [17]. In a comparative analysis of GWR and OLS methods, Propastin and Kappas [1] presented an application of the GWR regression model that could provide a more accurate prediction than the OLS regression model. The GWR model is a common form of statistical modeling that was applied in various fields of geographic applications. Previous studies have attempted to apply GWR models to assess the relationship between vegetation systems and meteorological factors. For instance, Zhao *et al.* [6] demonstrated that GWR could spatially reflect different effects of climate factors on the vegetation. Propastin and Kappas [1] pointed out that the spatial patterns in the intercept and slope parameters estimated from the GWR models revealed different responses of the vegetation to precipitation. Li and Meng [12] proved that the GWR model has the capacity of capturing the spatial and temporal heterogeneity patterns of forest dynamics to climatic changes.

Winter [25] explains the random effect as a factor that is usually nonsystematic and unpredictable and influences the data. The method for considering both fixed and random effects of coefficient estimation was known as the linear mixed effects model (LMM) [26]–[28]. LMM is applicable to a diverse set of applications and domains in the forestry. For instance, Moore *et al.* [29] incorporated random effects in regression models to account for the temporal autocorrelation in the phenological dynamics of vegetation. Additionally, to deal with spatial variabilities, LMM can relax the assumption of independence. For instance, LMM considers the spatial dependence and spatial heterogeneity in modeling processes to deal with the spatial effects of forests with different spatial patterns of tree locations [28], [31]–[33]. Previous studies have demonstrated that the LMM is capable of characterizing the variance parameters of random effects in model residuals and of obtaining more accurate predictions than those derived from general fixed effects models. For instance, the LMM method fitted data better than the OLS method as it emphasizes the local information through characterizing spatial covariance structure and removing the effects of spatial autocorrelation in model residuals [30]. Breidenbach *et al.* [34] found that the use of LMM can improve the estimates and reduce the bias, which is present in the estimates of fixed effects models. Meng *et al.* [28] pointed out that the LMM can more closely indicate the spatial characteristics of forest biomass than fixed effects models.

Understanding forest dynamics in relation to climate change is essential for analyzing the impact of forest changes on regional biodiversity [35]. By exploring the GOM forest variations under climate change conditions, this study provides a good understanding of the landscape dynamics of the GOM Coast region and helps to promote the sustainable development of the GOM ecosystems. The forests around the GOM are one of the most biologically diverse ecosystems and rely on favorable temperatures and appropriate precipitation patterns [36]–[39]. To study this region is valuable for understanding global climate change and its ecological consequences [11]. The coastal environments along the GOM are altered by the consequences of climate change [40]. As such, changes in the temperature and precipitation within the GOM coastal region were expected to be able to explain forest dynamics in this study. Previously, there have been many discussions on the spatiotemporal variation of vegetation in response to climate change using the multivariate regression analysis. However, the mixed effects of fixed and random impacts of variables have seldom been considered in the literature. To obtain an improved estimate of the relationship between forest dynamics and climate change, we hypothesized that both fixed and random effects exist in regression models that are used to explain forest dynamics. The goal of this study is to understand how forest dynamics are explained by meteorological factors that are influenced by underlying fixed and random effects. To achieve this objective, a comparative analysis was conducted to assess the model performance of the model using fixed effects variables, and the model of using both fixed effects and random effects variables and the coefficient of determination (R^2), The Akaike information criterion (AIC) and Bayesian information criterion (BIC) were generated for the model performance assessment. By using precipitation, temperature, and NDVI data ranging from March 2009 to February 2010, we intended to explore the importance of random effects to address forest dynamics within softwood, hardwood, and mixed forests dominated areas in the GOM coastal region. The model applied in this study to estimate forest dynamics will be a useful tool for assessing the GOM forest resilience to climate change.

II. Material and Methods

A. Study Area

A total of 244 counties were defined as the coastal counties that intersect an inland buffer area located 100 miles (approximately 160 km) from the coastline of the GOM (see Fig. 1). The major climate type of this area is humid subtropical [41]. The average annual precipitation is 1452 mm and the average annual temperature is 19.0 °C. The majority of precipitation occurs as rain throughout the whole year. The study area is mainly occupied by the forest and agricultural land uses extending from eastern Texas to the Florida Keys, which varies greatly due to the influential factors, such as climate change and human disturbance [39].

B. Data Source

We obtained meteorological data at 4-km grid cell resolution for a period from March 2009 to February 2010. The data included monthly precipitation and temperature obtained

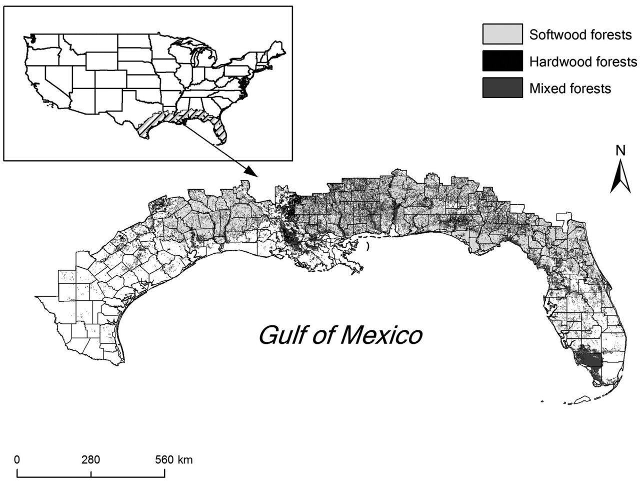

Fig. 1. Study area: the GOM coastal region.

from the parameter-elevation regressions on independent slopes model dataset, which was produced by the Natural Resources Conservation Service, National Water and Climate Center in partnership with Oregon State University. The byseason precipitation for spring (March–May), summer (June–August), fall (September–November), and winter (December–February) was generated separately through an accumulation of respective monthly precipitation values. The whole-year precipitation was defined as an accumulation of precipitation values from March 2009 to February 2010. Similarly, the byseason temperature was obtained through the computed averages of monthly temperature values. The whole year's temperature was obtained by averaging the temperature values from March 2009 to February 2010.

NDVI is one of the most widely used multispectral vegetation indices in remote sensing. It is formulated based on the reflectance measurements in the red and near-infrared portion of the spectrum. Forest biomass and dynamics characteristics could be represented by NDVI at the landscape scale [1], [17], [28]. In this study, we employed NDVI to quantify forest greenness and biomass. The NDVI data were obtained based on the MODIS 16-day composite NDVI (MOD13Q1) product at a 250-m spatial resolution. The monthly NDVI was generated using the two 16-day composite in a month period. To be consistent with the meteorological data, the preparation of the byseason and whole-year NDVI was implemented by averaging the 3 of and 12 of monthly NDVI values, respectively.

Propastin and Kappas [1] indicated that the magnitude and the sign of regression model parameters obtained at different locations could exhibit a large difference. Therefore, to improve the regression model performance and reduce the model variance the study area was classified into three forest types (i.e., softwood, hardwood, and mixed forests), according to the National Land Cover Database [42]. After removing invalid values, the precipitation, temperature, and NDVI were extracted from the byseason and whole-year raster data layers to an attribute table. The attribute was then aggregated, respectively, based on softwood, hardwood, and mixed forests dominated areas located across a total of 244 coastal counties for the regression analysis.

C. Linear Mixed Effects Models

An LMM is an expansion of a typical linear regression model. In the LMM, random effects refer to the effects of variables that are assumed to be a random sample varying randomly around a population mean [34]. The LMM can be written as a single combined model with fixed and random effects. The combined model is expressed as

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

$$\varepsilon_i \sim N\left(0, \sigma^2\right) \text{ i.i.d} \tag{2}$$

$$b_{0i} \sim N\left(0, {\sigma_{b_{0i}}}^2\right) \text{ i.i.d} \tag{3}$$

$$b_{1ij} \sim N\left(0, {\sigma_{b_{1ij}}}^2\right) \text{ i.i.d.} \tag{4}$$

Here, β_{0i} and β_{1ij} are the fixed effects coefficients to be estimated from data; b_{0i} and b_{1ij} are the random effects 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. In essence, each random effect unit has its random regression line such that the intercept is $\beta_{0i} + b_{0i}$ and the slope is $\beta_{1ij} + b_{1ij}$. The LMM could account for the variation by introducing random effects for the intercept and slope parameters [28], [29], [43]. In this study, the intercept and slope parameters of the model were assumed to vary randomly unit by unit in the LMM. Each random effect unit was assigned a different intercept and a different slope, as a result, NDVI could have different correlations with meteorological variables for different units. By incorporating random intercepts and slopes, the precipitation and temperature are allowed to account for NDVI variations across random effect units where the true distribution is unobservable due to the spatial dependence. The random effect unit can be an area where the observations were grouped into clusters resulting from the unobserved geographical factors, for instance ecological, geological, topographic, and soil conditions [28]. In this study, the linear mixed effects modeling was performed using the SAS MIXED procedure [44]. The variance components (VCs) structure was specified as the covariance structure, which models a different VC for each random effect unit.

To investigate the relationship between NDVI and meteorological variables, we regressed byseason and whole-year NDVIs against the precipitation and temperature. The mixed effects approach allowed us to account for the variation in NDVI by treating intercepts and slopes as random terms. Therefore, we proposed the following four options for the random configuration (see Table I).

1) The random intercept and random slopes of both precipitation and temperature, which included fixed coefficients, such as the random intercept and random slopes of both precipitation and temperature;
2) The random intercept and random slope of precipitation, which included fixed coefficients, such as a random intercept and a random slope of precipitation.

TABLE I
LINEAR MIXED EFFECTS MODELING OF FOREST DYNAMICS

	Model Name	Fixed-effects Variables	Random-effects Variables
Model 1	Random intercept and random meteorology model	precipitation and temperature	precipitation and temperature
Model 2	Random intercept and random precipitation model	precipitation and temperature	precipitation
Model 3	Random intercept and random temperature model	precipitation and temperature	temperature
Model 4	Random intercept model	precipitation and temperature	N/A

Four types of models are generally in two major forms: first, the random intercept and random slope model (e.g., Models 1, 2, and 3), which estimates separate slopes for each variable for each random effect unit and estimates separate intercepts for each random effect unit at which the slope and the intercept are allowed to vary; and second, the random intercept model (e.g., Model 4), which estimates separate intercepts for each random effect unit at which the intercept is permitted to vary.

3) The random intercept and random slope of temperature, which included fixed coefficients, such as a random intercept and a random slope of temperature.
4) The random intercept, which included a fixed intercept, such as a random intercept, and fixed slopes of both precipitation and temperature. For each forest type, linear regressions were performed and examined respectively.

D. Measures of Goodness of Fit

The overall model fitting was evaluated by three statistics, including R^2, AIC, and BIC, which are usually presented as model comparison tools for LMMs [28], [45].

The information criteria (e.g., AIC and BIC) were used to select the best models by comparing the models relative to one another. A smaller value of AIC and BIC suggests that the model explains the observed data better. AIC and BIC both consist of a calculation of the maximum log likelihood and a penalty term, and are represented by the following equations:

$$\mathrm{AIC} = -2\ln\left(\hat{L}\right) + 2k \tag{5}$$

$$\mathrm{BIC} = -2\ln\left(\hat{L}\right) + k\ln\left(n\right) \tag{6}$$

where ln() is a log function; L is the maximum likelihood estimate of parameters; k is the number of parameters in the model; n is the number of observations in the dataset.

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 residual variance, it is not entirely clear which to use when calculating R^2 values. Two easily interpretable values of R^2 have been derived by Nakagawa and Schielzeth [45]: the marginal R^2 (R^2m) describes the proportion of variance explained by the fixed factor(s) alone, which is useful in identifying the most parsimonious model; the conditional R^2 (R^2c) describes the proportion of variance explained by both fixed and random factors [46]. R^2m and R^2c are calculated by the following equations:

TABLE II
AIC, BIC, AND R^2 FOR THE FITTED MODEL OF SOFTWOOD FORESTS

Model	Season/Year	AIC	BIC	R^2c	R^2m
Model 1	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
Model 2	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
Model 3	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
Model 4	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

$$R^2m = \frac{\mathrm{var}_f}{\mathrm{var}_f + \mathrm{var}_r + \mathrm{var}_e} \tag{7}$$

$$R^2c = \frac{\mathrm{var}_f + \mathrm{var}_r}{\mathrm{var}_f + \mathrm{var}_r + \mathrm{var}_e} \tag{8}$$

where var_f is the fixed effects variance; var_r is the random effects variance; and var_e is the model residual variance.

III. RESULTS

By applying the NDVI and meteorological data from March 2009 to February 2010, the result showed that generally NDVI had a positive relationship with the precipitation and was negatively correlated with the temperature (see Fig. 2). For all three forest types, the explanatory variables were linearly and significantly ($p < 0.05$) correlated with NDVI.

By observing the variation of R^2 values, we found that the marginal R^2 values at the given season/year across four types of LMMs are the same and this is because of the fact that the marginal R^2 only describes the proportion of variance explained by fixed effects variables alone. The seasonal trend of the conditional and marginal R^2 values also indicated that the model performance varies slightly different from the seasonal patterns in NDVI, temperature, and precipitation. As outlined in Fig. 3, NDVI and temperature peaked in summer and dropped to the lowest value in winter, while the precipitation values in spring and winter are relatively higher than in summer and fall.

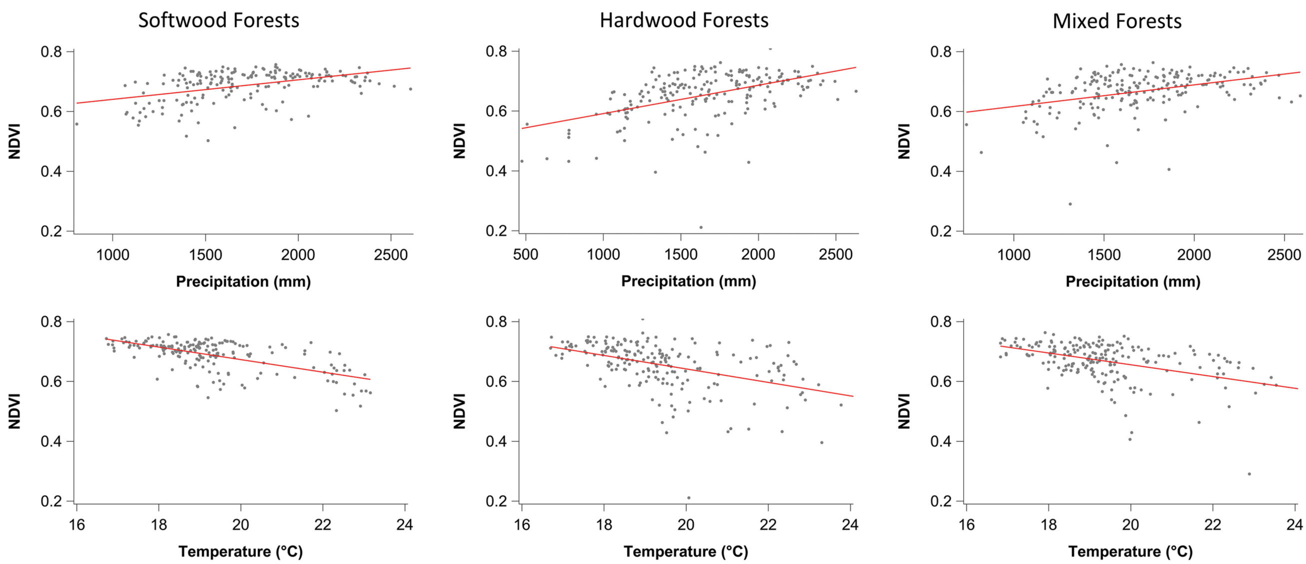

Fig. 2. Scatter plots of the precipitation and temperature against NDVI of softwood forests, hardwood forests, and mixed forests, from March 2009 to February 2010. For softwood forests, Pearson's r between NDVI and precipitation is 0.44 ($p < 0.0001$), and between NDVI and temperature is -0.62 ($p < 0.0001$). For hardwood forests, Pearson's r between NDVI and precipitation is 0.48 ($p < 0.0001$), and between NDVI and temperature is -0.45 ($p < 0.0001$). For mixed forests, Pearson's r between NDVI and precipitation is 0.39 ($p < 0.0001$), and between NDVI and temperature is -0.46 ($p < 0.0001$).

Regression results (see Tables II–V) showed that R^2 values are relatively higher in spring and summer than in fall and winter.

Table II indicates that by fitting the byseason data, both conditional R^2 and marginal R^2 showed a decrease of value from spring to winter in all models, which implies that the model using fixed effects variables, and the model using both fixed effects variables and random effects variables exhibited a similar pattern of changes in the byseason data fitting for softwood forests. The conditional R^2 value also indicates a slightly better fit of the whole-year data than the byseason data. The random intercept and random meteorology model provided the lower values of AIC and BIC, and the higher values of conditional R^2 compared with the random intercept model, which suggested that by considering random effects for both intercept and slopes, the models fitted data better, and the random effects from precipitation are not significant. Generally, the results indicate that for the spring softwood forest, the largest conditional R^2 value (0.63) was obtained from the whole-year data and the largest marginal R^2 value (0.49) was obtained from the spring data.

Table III indicates that by modeling the hardwood byseason data, the marginal R^2 value was found peaked in summer and then undergoing a decrease from summer to winter, which is consistent with the trends of changing NDVI and temperature. However, the conditional R^2 appears to be the highest in spring for hardwood forests. By incorporating random effects variables, the mixed effects model resulted in a decrease of conditional R^2 value from spring to fall and an increase from fall to winter. Comparatively, the largest conditional R^2 value was derived from the random intercept and random meteorology model, which integrating the random effects for both intercept and slopes, and the precipitation coefficient did not exhibit random effects. Also, the lowest AIC and BIC values obtained from the random intercept and random meteorology model suggested that the data were best fitted by integrating the random effect for both intercepts and slopes. In general, the LMM provided the largest conditional R^2 value (0.67) that was obtained from the spring data and the largest marginal R^2 value (0.58) that was obtained from the summer data.

TABLE III
AIC, BIC, AND R^2 FOR THE FITTED MODEL OF HARDWOOD FORESTS

Model	Season/Year	AIC	BIC	R^2c	R^2m
Model 1	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
Model 2	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
Model 3	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
Model 4	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

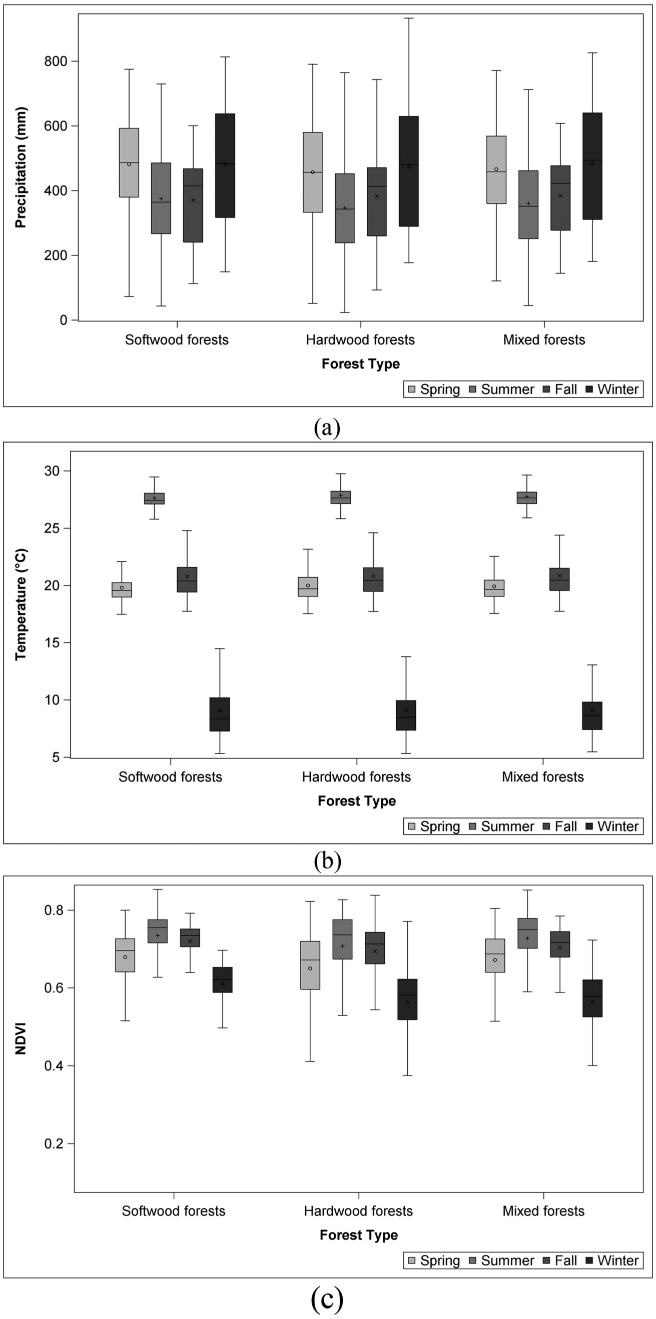

Fig. 3. (a) Byseason precipitation, (b) temperature, and (c) NDVI for three forest types: softwood forests, hardwood forests, and mixed forests.

In Table IV, both marginal R^2 and conditional R^2 indicate that the model was best fitted in summer. The marginal R^2 values imply that fixed effects could explain the most variance of summer mixed forest data. By integrating both fixed effects and random effects, the model resulted in the conditional R^2 values that were found the highest in the summer and lowest in the fall. Comparatively, the random intercept and random meteorology model exhibited the best fit of mixed forests' data but the precipitation coefficient did not show significant random effects. The highest conditional R^2 value was obtained from the random intercept and random meteorology model, which implies that the variation in NDVI could be best explained by integrating intercept and slope random effects. Moreover, the smallest AIC and the smallest BIC were derived from the random intercept and random meteorology model, which implies that considering random effects for both intercept and slope could improve the model fitting. Generally, the largest conditional R^2 value (0.56) and the largest marginal R^2 value (0.51) were both obtained from regressing the summer data.

TABLE IV
AIC, BIC, AND R^2 FOR THE FITTED MODEL OF MIXED FORESTS

Model	Season/Year	AIC	BIC	R^2c	R^2m
Model 1	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
Model 2	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
Model 3	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
Model 4	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

An overall result is presented in Table V after combining softwood, hardwood, and mixed forests' data. The results indicate that with both random effects and fixed effects variables, the random intercept and random meteorology model best fitted the data and could explain (conditional R^2) 54% of the variation in the whole-year NDVI. Table II also lists a difference between marginal R^2 and conditional R^2 values, indicating that by incorporating both random effects and fixed effects variables the LMM provides a better explanatory power in explaining the NDVI variations than by using only fixed effects variables. The difference also exists in AIC, BIC, and R^2 values between the random intercept and random temperature model and the random intercept model, suggesting that the two models are not equivalent in their explanatory power. Moreover, the model performance is different in explaining the seasonal forest dynamics, with the most explained variations in summer NDVI and least explained variations in fall NDVI.

Comparatively, the conditional R^2 values generally appear to be higher than the marginal R^2 values, which indicate a significant improvement in explaining the variations in NDVI

TABLE V
AIC, BIC, AND R^2 FOR THE FITTED MODEL OF FORESTS OF ALL THREE TYPES: SOFTWOOD FORESTS, HARDWOOD FORESTS, AND MIXED FORESTS

Model	Season/Year	AIC	BIC	R^2c	R^2m
Model 1	Spring	-1552.0	-1531.6	0.59	0.35
	Summer	-1724.4	-1704.0	0.60	0.52
	Fall	-2142.6	-2122.0	0.50	0.21
	Winter	-1327.5	-1307.1	0.52	0.01
	Year	-1700.4	-1680.0	0.54	0.27
Model 2	Spring	-1541.4	-1521.0	0.55	0.35
	Summer	-1721.1	-1700.7	0.56	0.52
	Fall	-2131.7	-2111.1	0.47	0.21
	Winter	-1312.1	-1291.7	0.45	0.01
	Year	-1687.1	-1666.7	0.49	0.27
Model 3	Spring	-1552.0	-1531.6	0.59	0.35
	Summer	-1724.4	-1704.0	0.60	0.52
	Fall	-2142.6	-2122.0	0.50	0.21
	Winter	-1327.5	-1307.1	0.52	0.01
	Year	-1700.4	-1680.0	0.54	0.27
Model 4	Spring	-1541.4	-1521.0	0.55	0.35
	Summer	-1721.1	-1700.7	0.56	0.52
	Fall	-2131.7	-2111.1	0.47	0.21
	Winter	-1312.1	-1291.7	0.45	0.01
	Year	-1687.1	-1666.7	0.49	0.27

by introducing both random effects and fixed effects variables. This finding is consistent with previous studies showing that mixed effects models fitted the data better than the fixed effects models in terms of R^2 values [30], [33]. The results obtained for three forest types were then compared with the amount of NDVI variance explained by each random intercept and random meteorology-slope model. The conditional R^2 value showed that the hardwood forests data were fitted better than the softwood forests data and the mixed forests data in spring, summer, and winter, while the softwood forests data were fitted better than the hardwood forests data and the mixed forests data during fall. In all three forest types, the models exhibited different explanatory power to explained NDVI variance with an apparent temporal heterogeneity. The best-fitted byseason model was obtained in spring for softwood forests, in spring for hardwood forests, and in summer for mixed forests, separately.

To determine the best-fitted LMM, we performed a comparative analysis based on AIC and BIC for determining whether to incorporate random effects for a slope (or slopes) of the meteorological factor(s) (e.g., precipitation, temperature, or both) in a given model. The results also imply an absence of random effects in the random intercept and random precipitation model, which suggested that the precipitation is not associated with random effects in fitted models. We then compared the AIC and BIC of two distinct types of resulting models: the random intercept model, and the random intercept and random slope model. This comparison indicated that the random intercept and random slope model is a more plausible one in terms of the lower AIC and BIC values. Second, to quantify the variance explained by fixed effects we employed both the marginal and conditional R^2 values to examine the goodness of fit of the random intercept model, and the random intercept and slope model. The value of R^2 derived from the random intercept and slope model was generally higher than the random intercept model indicating that the LMM with random effects on both intercept and slope best fits the data. This result also is similar to those found by Meng *et al.* [28] and Blundo *et al.* [47]. In summary, our results suggested that the random effects on the temperature could explain forest dynamics by using the random intercept and random slope model.

Table VI presented the differences between the model using fixed effects variables and the model incorporating both fixed effects and random effects variables. A comparative analysis illustrated that by considering the random effect on the temperature, the slope of regressing NDVI against the temperature by using both fixed effects and random effects variables was reduced by approximately 14%, 49%, and 7% of the slope values obtained by only using the fixed effects variables for softwood forests, hardwood forests, and mixed forests, respectively. Additionally, the residual standard deviation (RSD) represents the magnitude of the variation of the error term and the one of smaller value is preferred. The RSD value obtained by the model using both fixed effects and random effects variables reduced the value of RSD obtained by the model using fixed effects variables from 0.001664 (softwood forests), 0.004790 (hardwood forests), and 0.003238 (mixed forests) to 0.001008 (softwood forests), 0.002393 (hardwood forests), and 0.002877 (mixed forests), respectively, which indicated that by introducing the random effect of temperature, the linear mixed effect model could explain more variations of errors. Moreover, R^2 values of modeling fixed effects variables were found lower than the R^2 values of modeling both fixed effects and random effects variables, which is consistent with the finding by Orelien and Edwards [46] that the mixed effects model was fit more adequately than the fixed effects model.

IV. DISCUSSIONS

LMMs with forestry applications have been discussed by some scholars, most of which were conducted at the stand level [26], [34], [43], [48], [49]. An in-depth description of the LMM application at the regional level was given, for example, by Lu and Zhang [50], and Meng *et al*. [28], in which it was believed that the region-specific effect could be treated as a random effect in the mixed effects modeling. An important assumption behind the mixed effects modeling is that the effect of the variable occurring in groups varies randomly [34]. As a result, the models using both fixed effects and random effects variables could explain more variation of errors than only using fixed effects variables (see Table VI). This agrees with [19], which indicated that lacking the ability to adequately account for variability between region-specific groups, the fixed effects model results in a higher RSD than the mixed effects model. In this study, the regression results implied that the random effects associated with the temperature exist. However, the random effects associated

TABLE VI
MODEL COMPARISONS BETWEEN THE MODEL WITH FIXED EFFECTS AND RANDOM EFFECTS VARIABLES AND THE MODEL WITH FIXED EFFECTS VARIABLES WITHIN THREE DIFFERENT FOREST TYPES

	Softwood forests		Hardwood forests		Mixed forests	
	Model with fixed-effects and random-effects variables	Model with fixed-effects variables	Model with fixed-effects and random-effects variables	Model with fixed-effects variables	Model with fixed-effects and random-effects variables	Model with fixed-effects variables
Slope	-0.021540*	-0.018915*	-0.017990*	-0.012092*	-0.016090*	-0.015042*
R.S.D	0.001008	0.001664	0.002393	0.004790	0.002877	0.003238
R^2	0.63	0.39	0.63	0.27	0.31	0.24

$*p < 0.0001$. Results of the model with fixed effects and random effects variables displayed in Table VI were derived from the random intercept and random temperature model by regressing the whole-year NDVI against the whole-year temperature with random effects and fixed effects, and the whole-year precipitation with fixed effects. The results of the model with fixed effects variables displayed in Table VI were derived from the random intercept model by regressing the whole-year NDVI against the whole-year temperature with fixed effects and the whole-year precipitation with fixed effects.

with the precipitation were not found by using the LMM, which suggested that the random effect on the precipitation is constant and should be excluded from the LMM. Precipitation is the main source of water supply for vegetation dynamics over the North American continent [10]. It has been demonstrated that NDVI could be affected by antecedent precipitation events [21], [51]. In this study, the precipitation did not appear to be associated with NDVI in random effects modeling. It is likely due to the nature of the precipitation variables that the previous season's precipitation had time-lag effects on NDVI and the random effects of the current season's precipitation could not be observed immediately.

In this study, both marginal R^2 and conditional R^2 show seasonal variations, which is consistent with the finding of seasonal heterogeneity of correlations between NDVI and meteorological factors [7], [23]. Vegetative growth relies on carbohydrate metabolism and redistribution [52]. Seasonal climatic variations affect the distribution of carbohydrates in trees [53]. As a result, the vegetation has recurrent behaviors of suspending and resuming growth in response to seasonal changes in environmental conditions [54]. Normally, spring, summer, and early fall are suitable for tree growth, while unfavorable climate conditions during late fall and winter could lead to delays or even absence of tree growth [55]. The factors that give rise to the vegetation winter dormancy are complex and by altering the temperature and precipitation, climate change could influence the patterns of dormancy [56]. The marginal R^2 of winter exhibits a relatively smaller value than R^2 of other seasons, which implies that spring, summer, and fall data were fitted better than the winter data. The reason that the LMM exhibits a weak explanatory power for the winter data is likely due to GOM forests responding to unfavorable climatic conditions by halting the growth during winter. As a result, little forest dynamics can be explained by variations in the winter temperature and precipitation.

The study area is influenced by a massive amount of spatiotemporal contextual factors. Specifically, Li and Meng [8], and Barrow *et al.* [39] have noted that the variations in the plant community composition and structure of GOM coastal forests can be affected by not only the meteorological factors, such as precipitation but also soil conditions, such as soil texture, soil type, and soil moisture and disturbance events, such as development and logging. Our results showed that by incorporating both fixed effects and random effects variables the best-fitted model could explain 63% (softwood forests), 67% (hardwood forests), 56% (mixed forests), and 60% (all types of forests) of variations in NDVI separately. The unexplained variance of model residuals would be due to the effects of soil conditions and anthropogenic disturbances. For instance, Mather and Yoshioka [4] believed that the climate affects the vegetation not only directly through the impacts that climatic factors, such as temperature, exert on the growth and development of the vegetation but also indirectly through the influence that the climatic factors have on soil conditions. Moreover, vegetation responds to climate change in both explicit and unnoticed ways [14]. Therefore, due to the lack of byseason soil data and unknown of remained anthropogenic noise, the mixed effects model needs to incorporate more explanatory variables to explain the remaining variance of residuals.

By using fixed effects models, previous studies have found that the cause of the variance of relationships between NDVI and its meteorological factors could be spatial variations in vegetation types [10], [14], [15], [23]. This study takes random effects into account to explain the variations in NDVI through the utilization of the LMM for three forest types. The results showed that mixed effects models exhibited different explanatory power to explain softwood, hardwood, and mixed forest dynamics, which indicated that the model performance can be influenced by site conditions, such as forest types. This observation is consistent with a finding that climatic factors were observed to vary over space and time, and forest dynamics vary accordingly [12], [20], [22]. Zhang *et al.* [30] have pointed out that the model performance depended on the characteristics and nature of the spatial autocorrelation and heterogeneity of model residuals. For instance, Babst *et al*. [57] have demonstrated the responses of forest growth to seasonal climate controls are ecosystem dependent and can be highly site-specific and species-specific. The byseason and whole-year conditional R^2 obtained in this study showed a lower value in the mixed forests than that obtained in hardwood and softwood forests. We speculated that some forest-dominated areas might experience human-induced changes in forest dynamics. For instance, the replacement of mixed forests by evergreen forests in the coastal region of the GOM was attributed to the logging activities [58].

V. Conclusion

This study generally provides useful guidelines for choosing an appropriate model by using the LMM. We investigated the random effects from four distinct types of mixed effects models and the performance of the model was subsequently found depending on the presence of random effects. A comparative analysis of model performance indicates that random effects influence both the intercept and slope in regression models. The random intercept and random slope model best fitted the data regarding the larger conditional R^2, smaller AIC, and smaller BIC values, suggesting a significant improvement in the model fitting by accounting for the combined effects of random effects and fixed effects. The marginal R^2 value was found less than the conditional R^2 value in all three forest types, which demonstrated that applying mixed effects models could reduce the unexplained variance remained in fixed effects models.

The use of LMM provides an important tool to link forest dynamics to meteorological factors. Our study utilized LMM to explore the GOM coastal forest dynamics that occurred under climate change conditions. The best-fitted byseason LMM was obtained in spring for softwood and hardwood forests and in summer for mixed forests. The conditional R^2 value showed that the hardwood forests data were fitted better than the softwood forests data and the mixed forests data in spring, summer, and winter, while the softwood forests data were fitted better than the hardwood forests data and the mixed forests data during fall. Our results indicated that the mixed effects of temperature and the fixed effects of precipitation were identified as the main factors to explain forest dynamics. The explained variance of models was found varying between seasons and forest types. A presence of unexplained variance remained in LMMs indicated a need for further identification and exploration of potential random effects.

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