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THE INFLUENCE OF ENVIRONMENTAL VARIABLES ON THE HEIGHT GROWTH OF LOBLOLLY PINE (Pinus taeda) IN THE WESTERN GULF

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By

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ABSTRACT

Understanding the effects of environmental factors on stand growth is important in optimizing forest management plans. This study investigated the effects of soil and climate factors on the height growth (site index) of loblolly pine (*Pinus Taeda L.*) using data collected from permanent plots established in intensively-managed plantations across East Texas and Western Louisiana. The Chapman-Richards model was selected as the base model to describe the height-age relationships and important soil and climate variables were incorporated into the models as model parameter coefficient adjustors. Our results showed that the most important factors for predicting site index were nitrogen content of B horizon for soil and precipitation in spring and fall. Three models were developed, with one incorporating nitrogen of B horizon, one incorporating spring and fall precipitation, and the last one incorporating both the soil and climate variables. An increase in nitrogen content in B horizon and an increase in spring precipitation increased the tree height, but an increase in fall precipitation slowed tree height growth. The log-likelihood ratio tests showed that all three models had significantly smaller AIC than the base model. Compared to the base model, the three models also had larger model coefficient of determination (R^2), smaller root mean squared error, and bias. All three models can be used to estimate site index of intensively-managed loblolly pine plantations in the region, but data used in this study were not large, and, therefore, caution should be taken in their application.

Key words: height-age relationship, site index, soil and climate, growth and yield modeling, loblolly pine plantations.

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LIST OF ABBREVIATIONS

SI	Site Index
ANH	Ammonia content in A horizon (ppm)
BNH	Ammonia content in B horizon (ppm)
ACG	Carbon content in A horizon (%)
BCG	Carbon content in B horizon (%)
ANG	Nitrogen content in A horizon (%)
BNG	Nitrogen content in B horizon (%)
ASD	Sand content in A horizon (%)
BSD	Sand content in B horizon (%)
ACY	Clay content in A horizon (%)
BCY	Clay content in B horizon (%)
AST	Silt content in A horizon (%)
BST	Silt content in B horizon (%)
mApct	Average winter season mean precipitation (mm day^{-1})
mAtmax	Average winter season max temperature (^{0}C)
mAtmin	Average winter season min temperature (^{0}C)
mAtmean	Average winter season mean temperature (^{0}C)
mBpct	Average spring season mean precipitation (mm day^{-1})
mBtmax	Average spring season max temperature (^{0}C)
mBtmin	Average spring season min temperature (^{0}C)
mBtmean	Average spring season mean temperature (^{0}C)
mCpct	Average summer season mean precipitation (mm day^{-1})
mCtmax	Average summer season max temperature (^{0}C)
mCtmin	Average summer season min temperature (^{0}C)
mCtmean	Average summer season mean temperature (^{0}C)
mDpct	Average fall season mean precipitation (mm day^{-1})

mDtmax	Average fall season max temperature (^{0}C)
mDtmin	Average fall season min temperature (^{0}C)
mDtmean	Average fall season mean temperature (^{0}C)
mYpct	Average annual mean precipitation (mm day^{-1})
mYtmax	Average annual max temperature (^{0}C)
mYtmin	Average annual min temperature (^{0}C)
mYmean	Average annual mean temperature (^{0}C)

INTRODUCTION

Since industrial forest landowners in East Texas converted their non-planted timber stands to loblolly (*Pinus taeda L.*) and slash (*Pinus elliotti E.)* pine plantations, sizeable portions of the land are predominantly occupied by loblolly pine. This is estimated to occupy approximately 80 percent of the converted acreage (Clutter et al. 1983). To efficiently manage these plantations, developing models that can predict accurate and reliable stand structure information is indispensable.

To meet this need, the Arthur Temple College of Forestry at Stephen F. Austin State University (SFASU) and some forest management companies initiated the East Texas Pine Plantation Research Program (ETPPRP) in 1982 (Lenhart et al. 1985). This was to provide quantitative information for managing loblolly and slash pine plantations. During the Phase I study (1982 to 2015), over 260 plots were established in extensively managed (sites-treated with shearing, chopping, windrowing, and burning) loblolly and slash pine plantations across east Texas. Given the substantial changes in silviculture from extensive to intensive (e.g. sites receiving intermediate silvicultural treatments such as thinning, prescribed burning, fertilizer, or mid-rotation competition control) management beginning in the 1990s, a Phase II was established with 135 permanent plots in intensively managed pine plantations across east Texas and western Louisiana.

Site index (SI) is widely utilized to indirectly describe the growth potential of forestlands and several equations have been used to predict SI. Blackard (1986), Lenhart et al. (1986), Kallus (1989), and Coble and Lee (2006 & 2010) developed models that predicted SI using data from Phase I study which are extensively managed pine plantations. However, there is a dearth of models to predict the SI for intensively managed loblolly pine plantations. Priest et al. (2016) developed loblolly pine site index for reclaimed mine lands that underwent different soil replacement procedures. Recently, Trim et al. (2020) published a new site index model for intensively managed loblolly pine plantations in the region using data of ETPPRP Phase II plots. All these models, while focused on height-age relationships, did not account for environmental (e.g. soil and climate) influences on height growth.

Biophysical factors are important drivers of forest plantations and changes in these factors may influence plantations productivity (Sabatia & Burkhart, 2014). The relationships between biophysical factors and loblolly pine growth and survival in east Texas have been investigated; Brown (1994) examined the relationships between climatic variables (precipitation, temperature and number of rain days) and loblolly pine growth and mortality and found height growth was significantly affected by these variables. Beer (2009) analyzed the correlations between soil variables and SI for extensively managed loblolly pine and indicated that percentage of clay in the top soil was best predictor of SI. Both Brown (1994) and Beer (2009) focused on relationships between height growth and soil/climate variables of extensively managed plantations, without incorporating climate and/soil variables into SI models. Information regarding the effects of soil and climate variables on loblolly height growth by incorporating soil and climate variables into SI models for intensively managed loblolly pine plantations is lacking. Many factors, both biotic and abiotic, may influence the growth of pine, either positively or negatively. Therefore, incorporating climate and soil variables into SI models may improve our understanding of how these factors affect height growth and improve model efficiency.

In response, this study involved integrating selected abiotic factors, including soil properties and climate variables, into SI models to study their effects on height growth of pine plantations in east Texas and western Louisiana. Climate and soil data from the ETPPRP Phase II plots were used in the prediction models.

OBJECTIVES

The objectives of this research were to:

1) Develop a new SI model that incorporates climate and soil variables into SI models.
2) Investigate the relationships between tree height growth and climate and soil variables
3) Compare texture class of the soils to those obtained from USDA Natural Resource Conservation Services online database.

LITERATURE REVIEW

Overview

Loblolly pine is the most widely cultivated timber species in the Southern United States and is considered an important commodity because of its value (Schultz, 1997). Subjected to intensive breeding programs, it is widely planted for both pulpwood and solid wood products.

In southern United States (US), a significant proportion of forestlands is occupied by pine plantations. Forestlands were estimated to be about 214 million acres and this includes about 24.7 million acres of pine plantations and 35 million acre of naturally regenerated pine plantations (Zhao et al. 2016). Texas is a top manufacturing state for wood-based industries estimated to have over 14.2 million acres of commercial timberland from a total of about 59.7 million acres of forestlands (Joshi et al. 2014). The forest sector has been a valuable resource since its earliest days, playing a key role by contributing to the state’s history and to local economies. In east Texas, timberland occupies 23 percent of forestlands.

Most of these are loblolly pine plantations accounting for about 58 percent of the timberland area in east Texas, with an average of 35.8 tons per acre. Annual measurements and inventory prepared by the Texas A&M Forest Service in partnership with the U.S Forest Service in this region shows an estimated 434.6 billion tons of biomass on timberland in east Texas (49 percent of this are softwood species); with timberland averaging annual net-growth estimated at 14.98 million tons (87 percent of this are softwoods (Edgar and Zehnder 2015)).

Loblolly pine silviculture has improved substantially over the years. Prior to 1990, loblolly pine plantations in east Texas were generally managed extensively, i.e. sites were treated with shearing, chopping, windrowing, and burning, but usually no other treatments were applied (Colbert et al. 1990; Albaugh et al. 1998; Jokela and Martin 2000). Growth and yield (G&Y) models have been developed for extensively managed plantations in south US (Bennett et al. 1959; Coile and Schumacher 1964; Bennett 1970; Burkhart 1971), including east Texas (Lenhart, 1971). Starting in the 1990s, intensive management activities such as thinning, prescribed burning, fertilization, planting genetically improved seedlings, or mid-rotation competition control were widely applied (Fox et al. 2007). These intensive management practices are expected to enhance plantation productivity substantially. Therefore, growth and yield models for intensively managed plantations should be developed to reflect changes in silvicultural practices.

Site index (SI) is the most common metric used around the world to measure the potential of forest site quality. It aids in evaluating the quality of forest sites and helps determine optimal management options. SI is defined as the average height of dominant and co-dominant trees of a given species at a base age. Being species and region dependent, SI must be developed by individual species and region.

Methods for Site Index Model Development

The development of SI models started back in the early 1900s as tendencies to device various techniques for estimating site quality of plantation upsurge (Schnur 1937; Cooley 1958; Richards 1959; Chapman 1961; Carmean 1971). To develop a SI model, typically, a suitable mathematic function describing height-age relationships is selected, observed data are fit to the function to estimate the function parameters, and the function paired with parameter estimates (known as model) can be used to predict height growth (SI) of a site. While the above procedure is often used, many techniques have been proposed and applied to make the model flexible and accurate. Overall site index curves can be grouped into two types: anamorphic and polymorphic (Clutter et al. 1983; Avery and Burkhart 2002).

Anamorphic Model Methods

The anamorphic model method utilizes single pairs of height-age measurements collected from a larger number of sampling trees in temporary plots or via stem analysis. An average curve (guide curve) is determined using data based on the selected equation (function). The guide curve/equation is then scaled up and down to determine the height-age curves for selected values of SI. Thus, all the curves are parallel and proportional to each other. Various mathematical functions have been used, but two sigmoid functions, the Chapman-Richards (Richards 1959; Chapman 1961) and Von Bertalanffy (Von Bertalanffy 1951) are commonly used (Clutter et al. 1983).

The Chapman-Richard (Richards 1959; Chapman 1961) growth function was based on the first order ordinary differential equation. This can be expressed as:

$$H = b_0\left[1 - e^{-b_1(A)}\right]^{b_2}$$

where H is average height of dominant/codominant trees at age A (years), b_0, b_1 and b_2 are regression coefficients.

Assuming plantation age equals index age (A_I) and stand height equals site index (S_I), rearranging and solving for site index (S_I) gives:

$$S_I = H\left[\frac{1 - e^{-b_1(A_I)}}{1 - e^{-b_1(A)}}\right]^{b_2}$$

Lenhart et al. (1986) used the above Chapman-Richards equation to describe and develop SI equations that produced anamorphic site curves for pine plantations for the West Gulf Coastal region. Coble and Lee (2006) implemented a generalized sigmoid growth function to develop site index curves for loblolly pine plantations. Another site index model known for developing anamorphic site curves is the Schumacher (1939) model which included logarithmic transformation. Coile and Schumacher (1964) implemented this model in deriving site index and anamorphic growth curves for loblolly pine plantations. This method assumes that curves of height over age of different sites are the same, which, however, is rarely true. Therefore, the anamorphic SI models may not represent true forms of curves for different site indices (Kershaw et al. 2003).

Polymorphic Model Methods

Model forms with the polymorphic model method have the property that the shape of the height-age curve or the curve shape within the same index level varies with SI. Devan and Burkhart (1982) presented a method of developing polymorphic site index curves. Most SI models can be further transposed using different approaches in order to produce a polymorphic growth curve. Expansion of Schumacher (1939) model using a Generalized Algebraic Difference Approach (GADA) produces polymorphic height-age model. GADA is a generic technique that allows more than one parameter to be site specific. This approach is used to derive dynamic equations that are polymorphic, having variable asymptotes (Cieszewki 2000). McDill and Amateis (1992) developed and produced polymorphic site curves from a variant of Hossfeld function. Cieszewki (2001) examined several GADA formulation from which he developed dynamic equations and polymorphic SI curves for Douglas-fir. Unlike the anamorphic method, this method is more parsimonious and has an advantage because it can be used to generate different shapes of curves for different site indexes thereby making it more flexible.

Site Index Modeling Research for Loblolly Pine Plantations

Southern United States

Numerous SI models have been developed and used for predicting loblolly pine plantations across the southern United States. These SI models were developed using grow and yield data from different plantations, mostly southeastern US that had different stand conditions and sampled with different methods (Burkhart et al. 1981). Two mathematic functions, the Schumacher (Schumacher 1939) and the Chapman-Richard function (Richards 1959; Chapman 1961) have been widely used in developing SI curves for loblolly pine in southern US (Coile and Schumacher, 1964; Clutter and Lenhart, 1968; Lenhart, 1971; Smalley and Bower, 1971).

Amateis and Burkhart (1985) used a separable differential equation to develop loblolly pine site index curves, which were applicable on cutover site prepared lands in both Coastal and Piedmont regions. Popham et al. (1979) developed equations for loblolly pine on cutover sites in the Western Gulf region from which he indicated that the growth potential of the site could be represented more accurately with knowledge of older trees. The selection of suitable site trees is important and tree ages closer to the base age will yield more accurate estimates of the site index (Carmean 1975; Weiskittel et al. 2011b). Diéguez-Aranda et al. (2006) developed flexible SI models from four dynamic site equations. These site equations are base-age invariant, i.e. there is no alteration in the predicted height regardless of change in the common age value. However, none of these predictions was used specifically for the Western Gulf region.

More SI curves were developed for other different tree species in this region of the United States (Cooley 1958; Doolittle and Vimmerstedt 1960; Bennett 1963; Kulow et al. 1966; Beck 1971; Carmean 1971, 1972, 1978; Newberry and Pienaar 1978; Borders et al. 1984). Other site index curves can be found at the National Register of Site Index Curves References (https://esi.sc.egov.usda.gov/html/fsregref.htm. Accessed 15 December 2019).

East Texas

Growth and yield models were developed for old-field loblolly pine plantations common in east Texas in early 1970s (Lenhart 1972). Lenhart et al. (1986) developed the first growth and yield models for these plantations which outlined a site index equation for loblolly and slash pine on non-old fields based on the Richard's growth function. Their predictions was used to estimate productivity of the species at young age with minimal site preparation. Likewise, Hacker and Bilan (1991) developed height prediction curves for loblolly pine plantations conversions (natural pine stands to pine plantation). Their equation was based on the Chapman-Richard's function. Their results showed that conversion of forest lands to pine plantations would increase productivity potential. Priest et al. (2016) evaluated the site index for reclaimed mined land in this region. They observed that there was no difference in the site index of the plantation before and after the mining process. However, none of the aforementioned research accounted for both climate and soil factors that could also influence SI estimation.

Coble and Lee (2006) used a generalized growth function called Schnute growth function to develop site index curves for loblolly and slash pine in east Texas. The Schnute growth function is based on two first-order differential equations and combining the two together gives a second-order differential equation that describes the acceleration of growth (Coble & Lee, 2006). The Schnute growth function is expressed as;

$$H = \left\{Y_1^b + \left({S_I}^b - Y_1^b\right)\frac{1 - e^{-a(t-t_1)}}{1 - e^{-a(t_I - t_1)}}\right\}^{\frac{1}{b}}$$

where H is average height of the tallest 10 trees at time t, S is site index, Y_1 is average height of tallest 10 trees at time t_1, t_I is index age, a and b are constants. Solving for S gives:

$$S_I = \left\{Y_1^b + \left(H^b - Y_1^b\right)\frac{1 - e^{-a(t_I - t_1)}}{1 - e^{-a(t-t_1)}}\right\}^{\frac{1}{b}}$$

This model was fit to height-age data and produces SI curves ranging from 40 to 90 ft at base age 25.

In comparison, the Coble and Lee (2006) study provided new SI curves and equations that were an improvement of Lenhart et al. (1986) because the coefficient test proved significant and the height-age data used trees older than 25 years old. Trim et al. (2020) utilized the most recent data to analyze and compare four different models to determine a better SI model for growth prediction in this region.

However, all the site index modeling in this region focused on height and stand age relationships as variables in the prediction models.

Effect of Soil Factors on Tree Growth

Soils are complex organisms and the growth rates of trees are affected by soil conditions and characteristics. Soil properties that can limit plant growth can be either physical or chemical. Although soil properties vary with soil depth, the physical properties usually determine the suitability of soil as a growth medium.

The physical properties indicate how water and nutrients are distributed within the soil layers. This properties has a frame work of rock particles ranging in different sizes and texture. The fine textured soil have small particle size and tends to hold water and nutrients well. However, the coarse textures soils have large particle size and do not have good water and nutrient retention capacity. They are less compacted and tend to be well drained. However, a well aggravated soil is good for tree growth (McClurkin 1953). The capacity of a soil to hold water and mineral nutrient would depend on the physical structure of the soil.

The chemical properties are important and encompasses the availability of nutrient in the soil. They are also determined by the organic matter and humus content in the soil. This property have effect on the microbial communities and the biological processes occurring in the soils. These properties also play role as the essential nutrients supplied to a tree.

The mineral content having dominant occurrence affects nutrient release in the soil and the extent to which these minerals are dominant affects the nutrients in the soil. The bounding together of soil mineral and organic matter are caused by organic molecules and fungi which forms soil aggregates.

Temperature, water and carbon to nitrogen percentage ratio were important factors for tree growth (Levesque et al. 2015). Often, conditions that limit growth during the growing season are due to soil moisture and soil aeration, and both factors cannot be assessed directly in the field (Coile 1952; McClurkin 1953; Zachner 1958). Also, organic matter improves soil structure by increasing the moisture and nutrient holding capacity of coarse-textured mineral soils (Willet & Bilan, 1991). Although these silvicultural techniques have helped to improve soil composition which supports growth rate, the soil properties are still widely considered in site index models to forecast plantation growth patterns and yields.

Willett and Bilan (1991) analyzed the properties of four major soil series and their relationships to height growth of loblolly pine plantation in east Texas. The results indicated similar height growth responses across the soil series, but the reasons for the similarity response differed by four soil series. Three of the soil series indicated an increase in stand height due to an increase in moisture availability. Meanwhile, the result from the fourth soil series showed increased stand height was due to better permeability and aeration of the same soil-forming condition of the surface and subsurface soil layers. The soil factors controlling height growth are not dependent on one property but a combination of the soil properties including its structure, texture, porosity, etc.

Research has shown that productivity of pine plantations can be increased by improving soil conditions via silvicultural activities. Fox et al. (2007) reported the enhancement in the growth of pine trees as a result of an increase in soil available nutrients after the application of fertilizers in pine plantation. Site preparations such as thinning, mid-rotation, etc. have also yielded positive outcomes in the quality of pine plantation (Bailey et al. 1982; Clutter et al. 1984). Trim et al. (2020) reported increased in predicted height growth is due to the intensive management regimes.

Incorporating Soil Factors into SI

The soil properties that are most important for prediction are those that determine the amount of growing space for tree roots (Coile 1952; Carmean 1975), one of which is the depth of the surface soil. The depth of surface soil supports the root extensions of which the tree root is the significant pathway for water consumption. The roots extend in the soil to collect volumes of water so therefore good surface soil depth would allow for better water intake by the root. Likewise, soil water plays a key role in forest productivity because accessibility of oxygen and water to the roots is via the soil, however, the ability for soil to store water depends mostly on the soil physical properties (Beer 2009).

Several studies have attempted to relate SI to measured soil properties (Carmean 1975; Fontes et al. 2003). Beer (2009) used a regression model to examine the site index of loblolly pine in East Texas with edaphic conditions which included precipitation and available water capacity of the soil. His work denoted how seasonal rainfall and soil texture had significant effects on the height growth of pine. Subedi and Fox (2016) used two regression modeling approaches (ordinary and partial least square regression) to predict loblolly pine plantation SI from soil properties. The second approach produced a more accurate result that explained the multicollinearity causing erroneous exclusion of predictors with high significance.

However, difficulty in analyzing forest ecosystems with respect to site quality has been reported because of the complex relationship in the interaction among environmental factors (Landsberg et al. 2003; Dye et al. 2004). Bassett (1964) observed the significant effect of soil moisture availability on the diameter growth of loblolly pine and indicated that there was increase in the diameter of tree due to a high percent (above 65%) of moisture content. However, diameter growth ceased when the moisture content was below that level. Beer (2009) observed similar results for site index prediction for loblolly pine in East Texas, but he also indicated that soil texture gave better SI prediction compared to available water capacity.

Effects of climate factors on tree growth

Climate changes has dramatic effects on the growing nature of trees which may be due to unpredicted changes in one or two weather conditions. Coile (1935) reported that higher than average rainfall positively influenced the radial growth of loblolly pine while increased temperature had a negative effect. Similar findings were obtained in studies on loblolly pine in East Texas (Aguilar 1979; Chang and Aguilar 1980). Changes in climate conditions such as duration of the growing season, precipitation, and temperature variation influences the diameter, height, and other growth features of plantation trees (Weiskittel et al. 2011a, b; Burkhart and Tome, 2012; Sharma et al. 2015). Likewise constant seasonal changes occurring and weather conditions are bound to vary annually. These conditions include but not limited to rainfall, humidity, temperature, atmospheric water vapor in precipitation. Regular and moderate rainfall is vital for tree growth meanwhile excessive or shortage in the amount and period of rainfall can have a detrimental effect on the nature of trees' growth. Higher rainfall is typically attributed to over-saturated water vapor in the atmosphere from evaporation, and temperature increase tends to increase water evaporation which then causes an increase in precipitation. Total annual precipitation in the southern US increased at an average of 11.1% per century (CCD 2008). Brown (1994) indicated temperature, precipitation and the number of rain days had significant effects on loblolly pine growth rate. Zhou et al. (2019) study for Mongolian pine showed height growth was directly proportional to mean temperature increase and precipitation but a decline with increasing precipitation. Meanwhile, a study in the Northern Rocky Mountains of Idaho and Montana, US (Hankin et al. 2019) reported the decline in the growth rate of some tree species as a result of increased temperature in regenerated forests. Therefore, tree height growth estimating is sensitive to changes in climate conditions. In response to this, there is a need to improve the knowledge of the climate relationships and its effect on the height growth of trees by incorporating climate variables in site index models.

Incorporating Climate Factors into SI

In forest management, it is vital to consider incorporating climate variables into SI models to describe climate relationship with tree growth. Brown (1994) examined the statistical relationship between site index and different climate variables using analysis of covariance. In his study, different climate factors (temperature, precipitation, the total number of rain days) were integrated as variables in the regression analysis. All the temperature parameters were found to be highly significant except for the average summer temperature range. Monserud et al. (2008) showed how their linear regression model was used to predict the potential change in the lodge pole pine site index under climate change in Alberta. Sharma et al. (2015) developed models for stand height and SI equations that incorporated climate variables for jack pine and black spruce plantations. They considered two (2) climate scenarios that resulted in the reduction of heights for both species as compared with those under a no climate change scenario. Amateis et al. (2006) incorporated a surrogate of climate into a SI model using a regression equation. Latitude and longitude included as predictor variables increased the precision of the regression equation, resulting in considerable improvement in prediction accuracy.

Sabatia and Burkhart (2014) examined the site index of loblolly pine from biophysical variables using data from the natural range plantations across the Southern United States. Considering both intensively managed (IMP) and non-intensive managed (Non-IMP) plantations, they used Random Forest and factor analysis approaches to identify the important independent variables. These variables were fitted using parametric nonlinear regression and Random Forest models, with the latter exhibiting better fit and prediction statistics than the former. The important variables were annual precipitations, soil depth, soil available water capacity, growing season days index, and elevation for Non-IMP, while for IMP were summer precipitation, elevation, late summer precipitation, and summer maximum temperature. There was an increase in the number of variables important for Non-IMP compared to the number of variables for IMP. All these results showed the changes in site indexes indicated that biophysical factors play a role in forest productivity.

Other statistical models for predicting climate change effects on the height growth of loblolly pine in the southeastern US were reported. Farjat et al. (2015) used an approach (multiple linear regression models) in model selection and parameter estimation for predicting height growth of loblolly pine, while considering only climatic effect on the models. Their studies considered future climate scenarios having decreased precipitation and increased minimum and maximum temperatures. The results indicated increased height growth of loblolly pine relative to current climate condition in their environment, whereas a change in the location of the seed source to a colder northern region brought about the decline in height growth. On the other hand, seed sources from plantations in the northern region were switched and tested in the model to evaluate their height/growth performance on a region with a lower maximum and minimum temperature. It showed a decline in growth rate compared to the seed source from the later region meaning that seed sources perform better under their natural habitat.

In this respect, more investigation is needed to simultaneously incorporate environmental factors into SI models to observe their influence on the growth rates of intensively managed pine plantations in the West Gulf Coastal Plain region.

METHODS

Data used for this project includes height/growth data, soil variables data from the ETPPRP phase II plots (Figure 1) and climate data.

Between 2004 and 2017, the ETPPRP installed 135 Phase II permanent plots in intensively managed loblolly pine plantations. These plantations plots span across 14 contiguous counties in East Texas and 5 parishes in Western Louisiana across East Texas and West Louisiana with geographic location (UTM NAD 83 Zone 15) GPS coordinates (Figure 1). Of this, 126 plots were actively measured and 9 had been compromised. Each plot is approximately 100ft by 100ft (approximately 0.23acres). A three-year measurement cycle has been implemented since the inception of the program. (Coble D. W., The east texas pine plantation research project: accomplishments as of fall 2015, 2015)

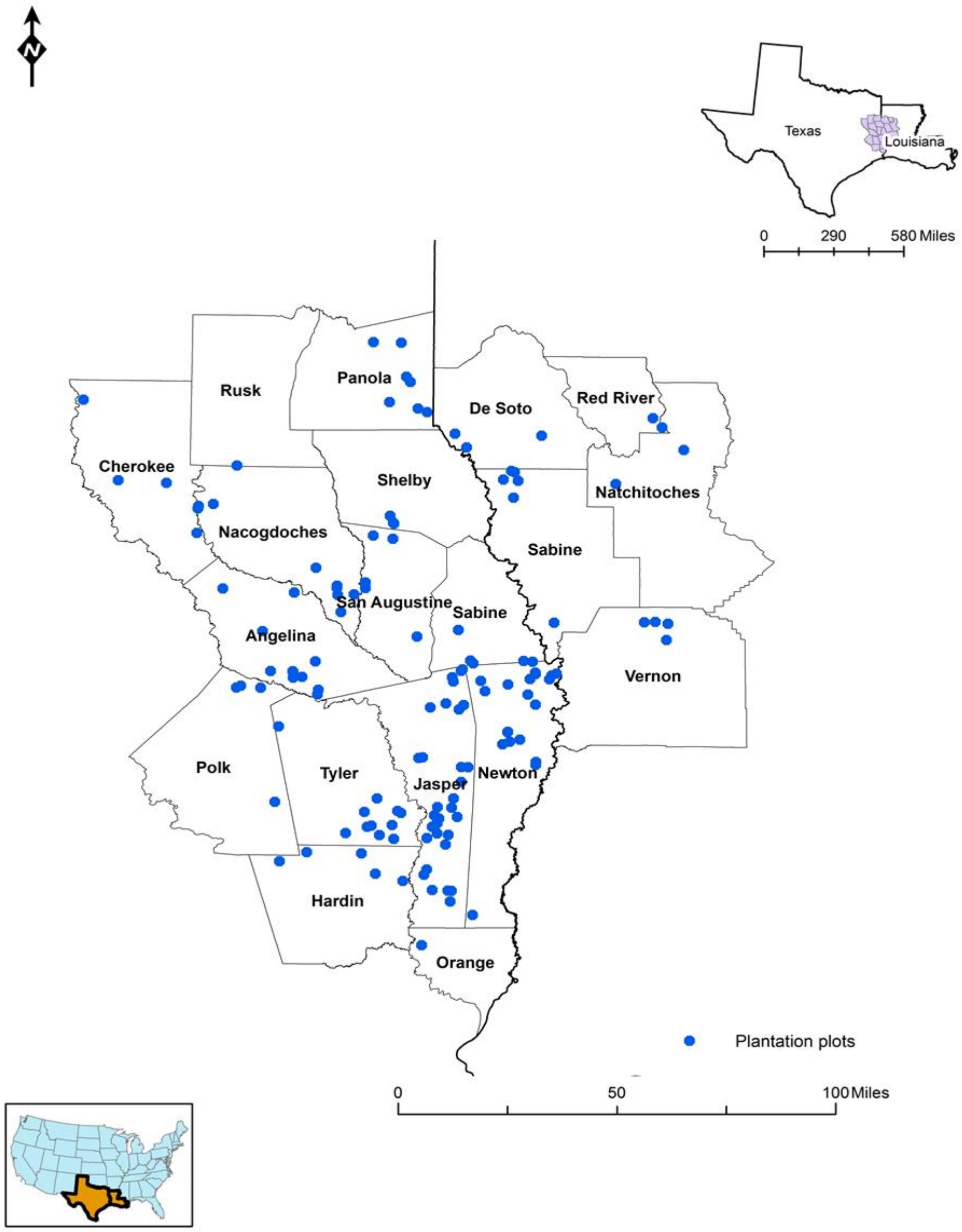

Figure 1. Spatial distribution of ETPPRP Phase II (135 plots) in East Texas and Western Louisiana.

Growth Data

The planted loblolly pine trees were permanently tagged and measured when the plots were installed, and measured every three years thereafter for diameter at breast height (DBH, nearest 0.1 inches), height (HT; nearest 1.0 foot), live crown length (nearest 1.0 foot), tree damaged/defect, and stand conditions. Individual tree data were first examined, outliers removed and then summarized to obtain plot dominant/codominant tree HT (ft), plot mean DBH (in), number of trees per acre (Tree ac^{-1}), and basal area ft^2 per acre (BA ac^{-1}). Plantation age (years) was determined as the time between the current measurement date and the plantation establishment date derived from stand records. At plot establishment, stand ages ranged between 2 to 22 years old, and stand density ranged between 139 and 838 trees ac^{-1}. On average, each plot was measured 5 times (cycles), ranging from 2 to 11 times. Dominant height (ft) was determined by averaging the total height of dominant and co-dominant trees that were free of damage (Avery & Burkhart 1983). More details of summary statistics of the plots including stand age, mean HT, Tree ac^{-1}, and BA $ft^2 ac^{-1}$ are provided in Table 1. In this study, a non-overlapped cycle-paired data set by plot, with a total of 469 observations, was formed and used.

Table 1. Observed stand characteristics for loblolly pine plantations ETPPRP Phase II plots.

Variable	SD	Mean	Minimum	Maximum
Age	3.94	8.12	2.00	22.00
HT	13.70	32.02	1.31	76.91
TPA	123.45	504.14	139.39	858.13
BAPA	44.33	75.03	1.20	184.30

NOTE: Age=plantation age (yrs.), HT=height of dominant and codominant trees (ft), TPA=trees per acre (ac^{-1}), BAPA=basal area per acre (ft^2ac^{-1}), SD=standard deviation.

Soil Data

Measured Data

During the collection of soil samples, only 119 plots were accessible and measured. At each plot, five sample points (located at four corners and the middle of the plot) were selected. Soil samples from the A and the first B horizon were collected using a bucket auger and transported in labeled soil samples bags. Each of the 5 samples per plot were composited by horizon divided into two parts (for chemical and physical analysis). A total of 476 samples were analyzed.

Chemical Properties Test

The soil chemical properties were measured in the Soil, Plant, and Water Analysis Laboratory at Stephen F Austin State University. The chemical properties that were analyzed included ammonium, total carbon content, and total nitrogen content for both A and B soil horizons. This was done because the growth rate response of loblolly pine has occurred with fertilizer additions of nitrogen, and ammonium is one form of nitrogen fixation (Beer, 2009).

All soil samples were air-dried and analyzed using a Leco CN628 instrument for total Carbon/Nitrogen content by way of combustion. The detectors in this instrument analyze the gases and processed by Leco’s software package. All the values were calculated and recorded.

Subsamples of the air-dried samples were mixed with an appropriate amount of buffer solution and reagents. This mixture stood for an estimated time depending on the temperature to allow color development, the absorbance was then read in the spectrometer. All samples were stirred before the Colorimetric determination for ammonium, outlined in procedures (Baethgen & Alley, 1989).

The analyzed soil chemical properties are summarized as:

Table 2. Summary of analyzed chemical properties of ETPPRP Phase II plots soil samples.

Variable	Mean	SD	Minimum	Maximum
ANH	4.43	2.83	0.19	17.02
BNH	3.65	3.57	0.16	29.10
ACG	1.64	0.65	0.56	3.94
BCG	0.91	0.30	0.48	2.39
ANG	0.17	0.04	0.08	0.29
BNG	0.14	0.02	0.09	0.24

NOTE: ANH= Ammonium content in A horizon (ppm), BNH= Ammonium content in B horizon (ppm), ACG= Carbon content in A horizon (%), BCG= Carbon content in B horizon (%), ANG= Nitrogen content in A horizon (%), BNG= Nitrogen content in B horizon (%).

Physical Properties (texture) Test

In the laboratory, soil samples from all plots were oven-dried at 105^0C to constant weight. To reduce the coherence of particles, the samples were ground. All dried soil samples were tested using the Bouyoucos hydrometer method. The resulting outcomes, expressed in percent sand, silt, and clay, were used in determining the individual textural classes for both horizon A and B from all plots samples. The soil texture classifications were defined through the fraction of each of the soil separates (percentages of sand, silt and clay) and aided with the use of soil texture triangle. Complete details of the physical properties test are outlined in Appendix 1.

Online Soil Data

Soil survey map data were retrieved from Web soil survey online source (Soil Survey Staff, USDA Natural Resources Conservation Service, United States Department of Agriculture, 2018). The soil data included were soil depth (to the 2-m USDA observation maximum); the name of soil series, soil available water storage capacity for the depth 0 – 150cm; particle percent clay, silt, sand, organic matter content, and soil textural classification. In the data system, soil properties data are associated with soil horizons, which are associated with a soil map unit (soil series).

Climate Data

Climate data for the ETPPRP phase II plots were obtained from the Oak Ridge National Laboratory Distributed Archive Center (Thornton, et al., Daymet: Monthly Climate Summaries on a 1-km Grid for North America, Version 3, 2016), known as DAYMET data. These annual climatology summaries are derived from the much larger data set of daily weather parameters, which are produced on a 1km by 1km grid surface over North America. The data set covers the period from January 1st, 1980, to December 31st, 2017. The data set obtained was transformed via spatial interpolation to create spatially and continuous climate data. This process converts irregularly spaced point data into a regularly shaped grid. The data collected were daily precipitation, minimum, mean, and maximum temperature. The temperature and precipitation used for this study ranged from January 1st, 2000, to December 31st, 2017. NB: This time range is not dependent on the time of plots/plantation establishment but the period is chosen to reflect considerable climate change over time. The climate variables retrieved were processed seasonally for winter, spring, summer, fall, and yearly average values. Winter denoted “A” was defined as the season starting from the first day of December through the last day of February. Spring denoted “B” was defined from the first day of March to the last day of May. Summer denoted “C” was defined as the season starting on the first day of June through the last day of August. Fall denoted “D” season was defined from the first day of September through the last day of November and annually denoted “Y”. Description of climate variables (Appendix 2) used was expressed as:

- Mean winter precipitation (mApct, mm day^{-1}): Average daily precipitation between Dec to Feb for year 2000 - 2017
- Mean winter maximum temperature (mAtmax, ^{0}C): Average daily maximum temperatures between Dec to Feb for year 2000 - 2017
- Mean winter minimum temperature (mAtmin, ^{0}C): Average daily minimum temperatures between Dec to Feb for year 2000 - 2017

- Mean winter mean temperature (mAtmean, ^{0}C): Average daily mean temperatures between Dec to Feb for year 2000 - 2017
- Mean spring precipitation (mBpct, mm day^{-1}): Average daily precipitation between Mar to May for year 2000 – 2017
- Mean spring maximum temperature (mBtmax, ^{o}C): Average daily maximum temperatures between Mar to May for year 2000 – 2017.
- Mean spring minimum temperature (mBtmin, ^{0}C): Average daily minimum temperatures between Mar to May for year 2000 - 2017
- Mean spring mean temperature (mBtmean, ^{0}C): Average daily mean temperatures between Mar to May for year 2000 - 2017
- Mean summer precipitation (mCpct, mm day^{-1}): Average daily precipitation between Jun to Aug for year 2000 - 2017
- Mean summer maximum temperature (mCtmax, ^{0}C): Average daily maximum temperatures between Jun to Aug for year 2000 - 2017
- Mean summer minimum temperature (mCtmin, ^{0}C): Average daily minimum temperatures between Jun to Aug for year 2000 - 2017
- Mean summer mean temperature (mCtmean, ^{0}C): Average daily mean temperatures between Jun to Aug for year 2000 - 2017
- Mean fall precipitation (mDpct, mm day^{-1}) Average daily precipitation between Sept to Nov for year 2000 – 2017

- Mean fall maximum temperature (mDtmax, ^{0}C): Average daily maximum temperatures between Sept to Nov for year 2000 - 2017
- Mean fall minimum temperature (mDtmin, ^{0}C): Average daily minimum temperatures between Sept to Nov for year 2000 - 2017
- Mean fall mean temperature (mDtmean, ^{0}C): Average daily mean temperatures between Sept to Nov for year 2000 - 2017
- Mean Annual precipitation (mYpct, mm day^{-1}): Average of daily precipitation over the year 2000 - 2017
- Mean Annual maximum temperature (mYtmax, ^{0}C): Average of daily maximum temperature over year 2000 - 2017
- Mean Annual minimum temperature (mYtmin, ^{0}C): Average of daily minimum temperature over year 2000 - 2017
- Mean Annual average temperature (mYtmean, ^{0}C): Average of daily mean temperature over year 2000 - 2017

Model Development

Analysis of the height growth of pine was accomplished using a regression model. A base model selected from an algebraic equation method derived by Chapman-Richards's function (Coble & Lee, 2006; Lenhart et al. 1986) was used as the base model:

$$H = \beta_0\left[1 - e^{-\beta_1(t - t_0)}\right]^{\beta_2} \quad (1)$$

Where H is the average height of dominant and codominant trees at time t, and t_0 is time at initial; β_0, β_1 and β_2 are respectively growth rate parameters.

An anamorphic SI curve can then be developed (Clutter et al. 1983) specifying SI in terms of a mathematical function. Defining an index age with SI as average heights of dominant and co-dominant trees, the Chapman-Richard growth function from Eqn. (1) can be expressed as:

$$S_I = \beta_0\left[1 - e^{-\beta_1(t_I - t_0)}\right]^{\beta_2} \quad (2)$$

where S_I is SI in feet at index age t_I and the other parameters are defined as previously.

From equation (2), making β_0 subject of formula we have;

$$\beta_0 = S_I\left[1 - e^{-\beta_1(t_I - t_0)}\right]^{-\beta_2} \quad (3)$$

then substituting β_0 into equation (1), and rearranging to solve for S_I, we have

$$S_I = H\left[\frac{1 - e^{-\beta_1(t_I)}}{1 - e^{-\beta_1(t)}}\right]^{\beta_2} \quad (4)$$

Equation (4) represents a family of anamorphic SI curves described by Chapman-Richards's growth function (Lenhart et al. 1986; Coble and Lee, 2006). To estimate the growth coefficients β_1 and β_2, initial values were selected based on previous publications (Lenhart et al. 1986; Coble and Lee, 2006). Consecutive iterations were processed with the resulting parameter estimates used as the initial parameter values in subsequent iteration procedures. The estimated coefficients were determined when the iteration processes attained convergence criterion. The coefficient parameters (β_{1j} and β_{2k}) for each plot were determined using similar procedures.

The base model (equation 4) did not account for variation among plots (site), thus in the next step random plot to plot variation was further incorporated into the model (4). Equation (4) was expressed in three different forms as:

$$S_I = H\left[\frac{1-e^{-(\beta_1+u_1)(t_I)}}{1-e^{-(\beta_1+u_1)(t)}}\right]^{\beta_2} \tag{5}$$

$$S_I = H\left[\frac{1-e^{-\beta_1(t_I)}}{1-e^{-\beta_1(t)}}\right]^{\beta_2+u2} \tag{6}$$

$$S_I = H\left[\frac{1-e^{-(\beta_1+u_1)(t_I)}}{1-e^{-(\beta_1+u_1)(t)}}\right]^{\beta_2+u2} \tag{7}$$

where u_1 and u_2 were random effects for β_1 and β_2 respectively, and other parameters remained the same as previous. It was defined that u_1 and u_2 was normally distributed and independent (NID), i.e. u_1~NID (0, σ_1^2), and u_2~NID (0, σ_2^2). Effects of u_1 and u_2 were evaluated based on their *p*-values (α=0.05) and by comparing each (models 5, 6, and 7) with model 4. The models with significant effects were kept, and the best model was selected for further analysis.

Model 4 was first applied to each plot data to predict model parameters. Preliminary correlation analyses among plot parameter estimates with soil and climate variables were done to identify key soil and climate variables. The variables that indicated relatively strong correlations with parameter estimates were identified as potential soil and climate variables. To model their effect by incorporating the selected soil and climate variables, the growth parameters in model 4 were expressed in terms of soil and climate variables with to time as:

$$\beta_1 = \left[(\beta_a + u_{1i}) + \beta_{1j}C_{1j} + \beta_{1k}S_{1k}\right] * t \qquad \text{or,}$$

$$\beta_1 = \left[(\beta_a + u_{1i}) * t + \beta_{1j}C_{1j} + \beta_{1k}S_{1k}\right]$$

and,

$$\beta_2 = \left[(\beta_b + u_{2i}) + \beta_{2j}C_{2j} + \beta_{2k}S_{2k}\right]$$

where β_a and β_b are the global estimates for β_1 and β_1, respectively, u_{1i} and u_{2i} are the random plot effect for β_1 and β_2, C_{1j} and C_{2j} are the jth selected climate variables, S_{1k} and S_{2k} are the kth selected soil variables, and β_{1j}, β_{1k},β_{2j}, and β_{2k} are the plot by plot model coefficients.

The selected soil and climate variables were incorporated into the best model of the models 5-7. For example if model 7 was selected, then soil and climate variables would be incorporated into model 4 the following ways:

$$S_I = H\left[\frac{1 - e^{-[(\beta_1 + u_{1i}) + \beta_{1k}S_{1k}]*(t_1)}}{1 - e^{-[(\beta_1 + u_{1i}) + \beta_{1k}S_{1k}]*(t)}}\right]^{(\beta_2 + u_{2i}) + \beta_{2k}S_{2k}} + e$$

or,

$$S_I = H\left[\frac{1 - e^{-[(\beta_1 + u_{1i})*t_I + \beta_{1k}S_{1k}]}}{1 - e^{-[(\beta_1 + u_{1i})*t + \beta_{1k}S_{1k}]}}\right]^{(\beta_2 + u_{2i}) + \beta_{2k}S_{2k}} + e$$

and,

$$S_I = H\left[\frac{1 - e^{-[(\beta_1 + u_{1i}) + \beta_{1j}C_{1j}]*(t_I)}}{1 - e^{-[(\beta_1 + u_{1i}) + \beta_{1j}C_{1j}](t)}}\right]^{(\beta_2 + u_{2i}) + \beta_{2j}C_{2j}} + e$$

or,

$$S_I = H\left[\frac{1 - e^{-[(\beta_1 + u_{1i})*t_I + \beta_{1j}C_{1j}]}}{1 - e^{-[(\beta_1 + u_{1i})*t + \beta_{1j}C_{1j}]}}\right]^{(\beta_2 + u_{2i}) + \beta_{2j}C_{2j}} + e$$

for soil and climate.

where e random error.

All model fittings were carried out using a non-linear mixed approach (PROC NLMIXED of SAS version 9.4). PROC NLMIXED uses a method of maximum likelihood to fit nonlinear mixed models with fixed and random effects.

Model Evaluation

Model fitness was evaluated by calculating model bias, Root Mean Square Error (RMSE) and the coefficient of determination R^2 using the following equations:

Mean Bias $= \frac{1}{n}\sum_{i=1}^{n}(Z_i - \hat{Z}_i)$,

RMSE = $\sqrt{\frac{\sum_{i=1}^{n}(Z_i - \hat{Z}_i)^2}{n-p}}$

and

$R^2 = 1 - \frac{\sum_{i=1}^{n}(Z_i - \hat{Z}_i)^2}{\sum_{i=1}^{n}(Z_i - \bar{Z}_i)^2} = 1 - \frac{SS_{res}}{SS_{tot}}$

where Z_i, $\bar{Z}_i$ and $\hat{Z}_i$ are the i^{th} observed height, mean of observed height and the model predicted height, respectively, n is the number of observations and p is the number of estimated parameters in the equation, SS_{res} is the residual sum of squares and SS_{tot} is the total sum of squares. Note that the model accuracy was evaluated by the model bias and model precision. Both RMSE and R^2 often show model precision; with smaller RMSE or larger R^2 indicating higher precision. R^2 shows the proportion of variance for a dependent variable being explained by the model (Steel and Torrie, 1960).

The Akaike Information Criterion (AIC) value was used to compare the pool of models, with the lowest ranking AIC model selected as best the best fit. AIC estimates the amount of information lost by a model during iteration processes. Log-likelihood ratio test was used to test statistical significance between two nested models, e.g. the base model and resulting model.

RESULTS

Soil Properties

Soil composition and properties (chemical and physical) varied greatly by plot (Appendix 1). As expected, the depth and thickness of B horizons were greater than those of A horizons across all plots. The depth of A horizons ranged from 0 inch to about 30 inches while the depth of B horizon ranged from 6 inches to greater than 35 inches. The chemical properties that were tested for in both A and B horizons included, total percentage available carbon and nitrogen and parts per million (ppm) ammonium. Our results indicated that, unlike the respective horizon thicknesses, most chemical tested results of horizon A had higher values that outcomes of horizon B. The result from the soil physical analysis indicated that for A horizon, about 34% of the plots had a texture of sandy loam, 39% had a texture of loamy sand, and 5% had a texture of sandy clay loam, and the corresponding values for B horizon were about 37%, 16% and 12% respectively (Table 3).

Table 3. Summary of soil texture classification of ETPPRP Phase II plots samples in percentages

Textural class	A horizon (%)	B horizon (%)
Sandy loam	34	38
Loamy sand	39	16
Sandy clay loam	5	12
Loam	2	6
Sand	5	3
Clay	0	6
Clay loam	1	2
Sandy clay	2	5
Unidentified	12	12

NOTE: Unidentified texture class are samples of ETPPRP Phase II inaccessible plots.

The texture class from the result of soil analysis were compared to those from online data sources. While most plots displayed the same texture classes between the laboratory analysis and online data (Appendix 3) - inconsistences were identified in some plots (203, 205, 218, 221, 227, 240, 248, 256, 258, 265, 277, 295, 300 and 317). There were more inconsistences in the B horizons as compared to the A horizon.

Model Development

Base Model

The growth data were fitted into the function (Eqn 4) and resulted in the final parameter estimates of β_1=0.05813 and β_2=1.0738. The model was:

$$S_I = H\left[\frac{1-e^{-0.05813(t_I)}}{1-e^{-0.05813(t)}}\right]^{1.0738} \quad [8]$$

Both parameters were significantly different from zero (Table 4). The model had a residual variance of 9.13 ft^2, R^2 of 0.94, BIAS of 0.03 ft, and RMSE of 3.02 ft. The model predicted the height well at both low and high ends of the data range but minimized those of the middle range (Figure 2). Model residual indicate that the model assumption of independence was violated to somewhat level (Figure 4) but assumptions of normality and equal variance were acceptable.

Table 4. Parameter estimates and confidence limits for base model (equation 4).

Parameter Estimates						
Parameter	Estimate	Standard Error	t Value	Pr > |t|	95% Confidence Limits	
β_1	0.058	0.006	10.21	<.0001	0.047	0.069
β_2	1.074	0.027	39.52	<.0001	1.021	1.127
s2e	9.134	0.596	15.31	<.0001	7.962	10.307

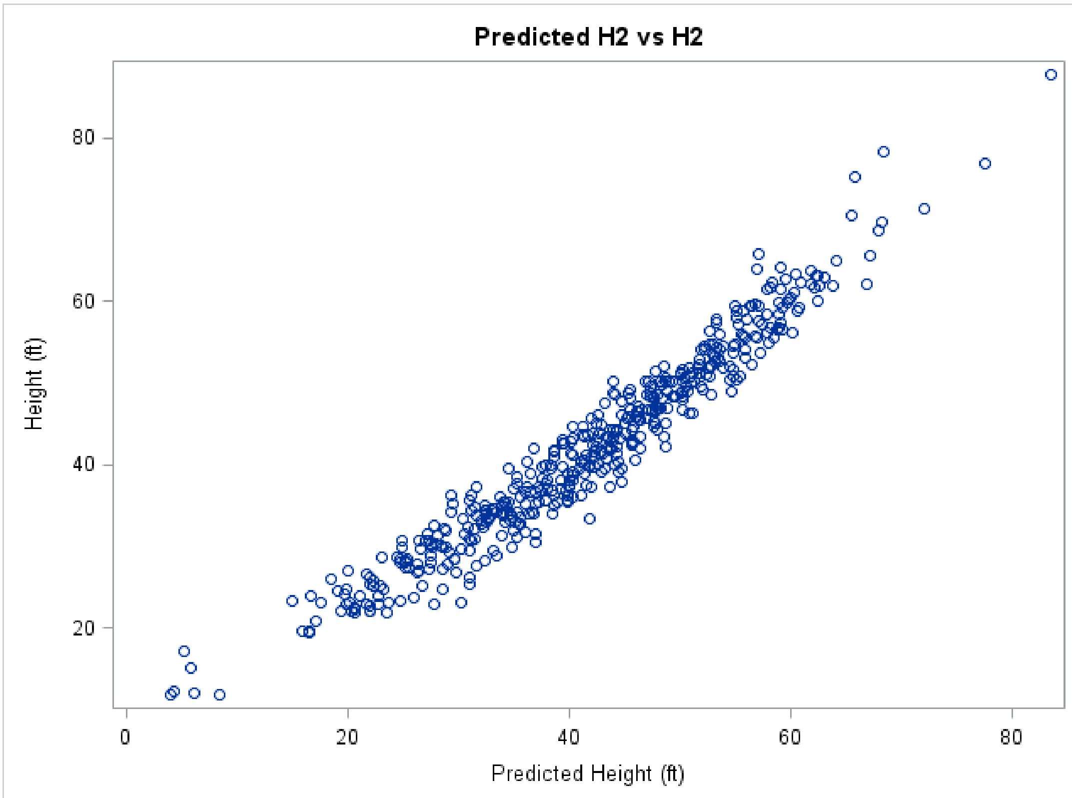

Figure 2. Plot of total height against predicted height of trees using the base model [8].

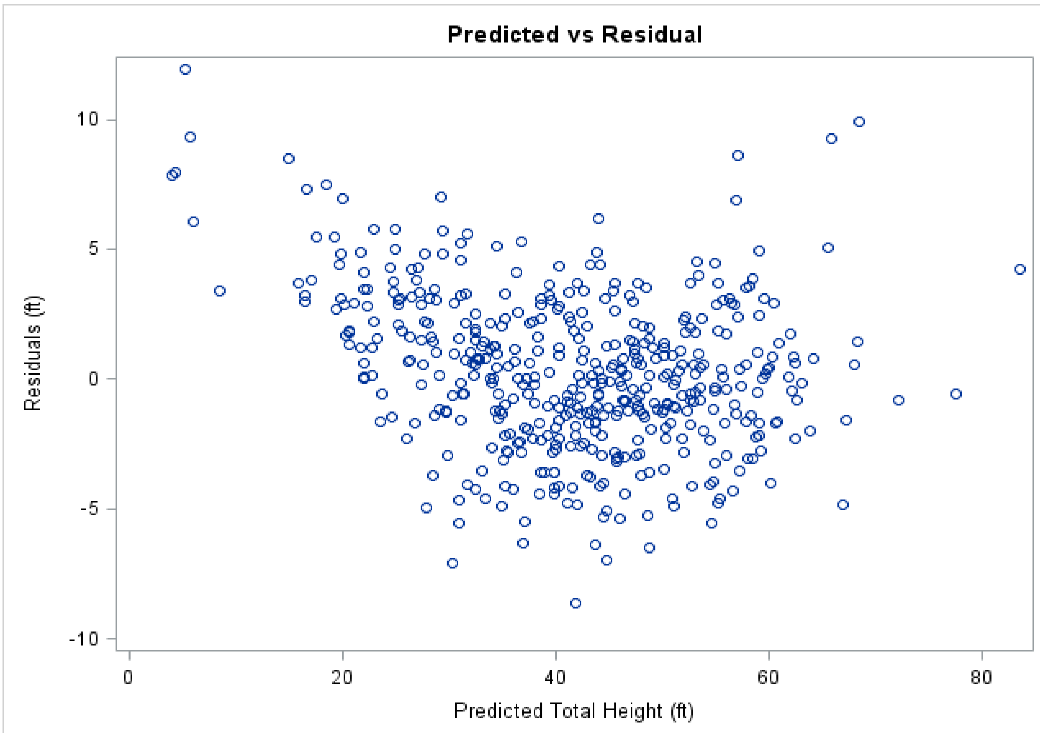

Figure 3. Plot of residuals against predicted total tree height from the base model [8].

The model was compared to the previous model by Lenhart et al. (1986), which was developed using the same mathematical function (Eq. 4) but they used data collected from extensively-managed loblolly pine plantations in the region. Using our base model and the Lenhart et al. (1986) model which had β_1 of 0.08005 and β_1 of 1.02857, we estimated total height values for pine plantation between 1 – 5 years for 5 site index classes (Table 5). We demonstrated predicted of total height values against plantation ages using anamorphic site curves (Figure 4). Our model predicted a larger HT than Lenhart et al. (1986) at a given age, reflecting the enhanced growth from extensively to intensive-managed plantations.

Table 5. Average height (in ft) comparison of ten tallest trees by SI for ages 1 – 5 years of loblolly pine between Lenhart et al. (1986) and base model (equation 4).

Species	Plantation age (yr)	Site index(ft)									
		40	50	60	70	80	40	50	60	70	80
		Lenhart et al. (1986)					Base model				
Loblolly	1	0.80	1.00	1.20	1.40	1.60	2.40	3.04	3.65	4.26	4.86
	2	2.30	2.80	3.40	4.00	4.50	5.73	7.16	8.59	10.02	11.46
	3	4.10	5.10	6.20	7.20	8.20	7.40	9.30	11.17	13.03	14.89
	4	6.20	7.70	9.20	10.80	12.30	9.80	12.30	14.75	17.20	19.70
	5	8.30	10.4	12.50	14.60	16.60	12.13	15.16	18.19	21.23	24.26

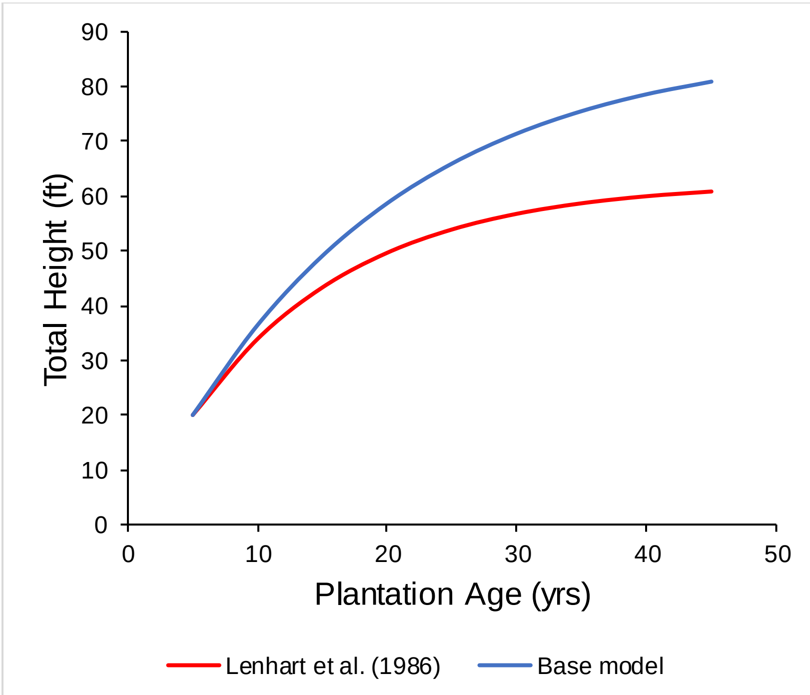

Figure 4. Comparison between Lenhart et al. model (1986) and base model [8] using anamorphic site index curves.

Model Accounting for Plot to Plot Variation

The base model did not account for the variation from plot to plot. In this step, we incorporated plot to plot variation into the model by adding random effects into the model where u_1 and u_2 were the random coefficients of β_1 and β_2 to reflect the plot to plot variation.

Data were fitted to equations (5) and (6) and results were summarized in Table 6. All model parameter estimates were significantly different from zero (0). The resulting residual variance from equation (5) was 9.13ft^2 and that of equation (6) was slightly smaller, 8.47ft^2.

Table 6. Itemized parameter estimates for equations (5) and (6).

Parameter Estimates						
Model	Parameter	Estimate	Standard Error	t Value	95% Confidence Limits	
Equation [5]	β_1	0.058	0.006	10.21	0.047	0.069
	β_2	1.074	0.027	39.52	1.020	1.128
Equation [6]	β_1	0.063	0.006	10.38	0.051	0.075
	β_2	1.102	0.031	35.05	1.039	1.164

We compared models (Equation 5) and (Equation 6) to the base model [8]. The log-likelihood ratio test showed that plot-to-plot variation in β_1 (U_1) was negligible but was significant for β_2 (U_2) (Table 7).

Data were also fitted into model (Equation 7) which integrated both random effect coefficients into the base model concurrently. However, this incorporation, although resulted in lower BIAS and RMSE than the base model , did not achieved a significant improvement over the base model based on the likelihood ratio test (Table 7) and even obtained a larger AIC than equation (6).

Table 7. Goodness of fit comparison amongst equation (5), (6) and (7) and base model [8].

Model	R^2	Bias (ft)	RMSE (ft)	AIC	Log-likelihood ratio test p-value with base model
Base [8]	0.94	0.03	3.02	2374.4	
Equation (5)	0.94	0.05	3.02	2376.4	1.00
Equation (6)	0.95	0.00	2.82	2372.2	0.04
Equation (7)	0.95	0.00	2.82	2376.2	0.25

Our results indicated Model (Equation 6) fitted the data best having a better goodness of fit. Model (Equation 6) was expressed as;

$$S_I = H\left[\frac{1- e^{-0.06259(t_I)}}{1- e^{-0.06259(t)}}\right]^{1.1019+u2} \quad [9]$$

Figures 5 and 6 showed model residual and assumptions were violated to somewhat level. Compared to the base model, incorporating plot-to-plot variation in the β_2 improved model assumptions and predictions slightly. Thus, model [9] was used as the model for incorporating soil and climate variables.

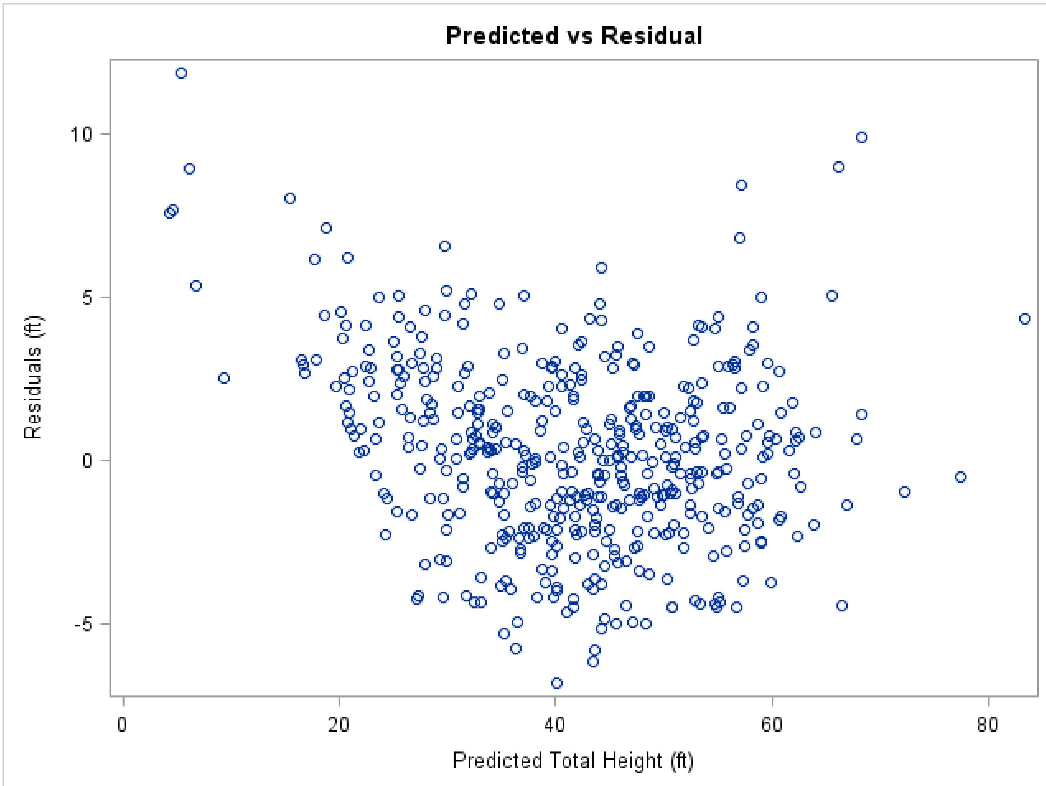

Figure 5. Plot of residuals against predicted total tree height from model [9].

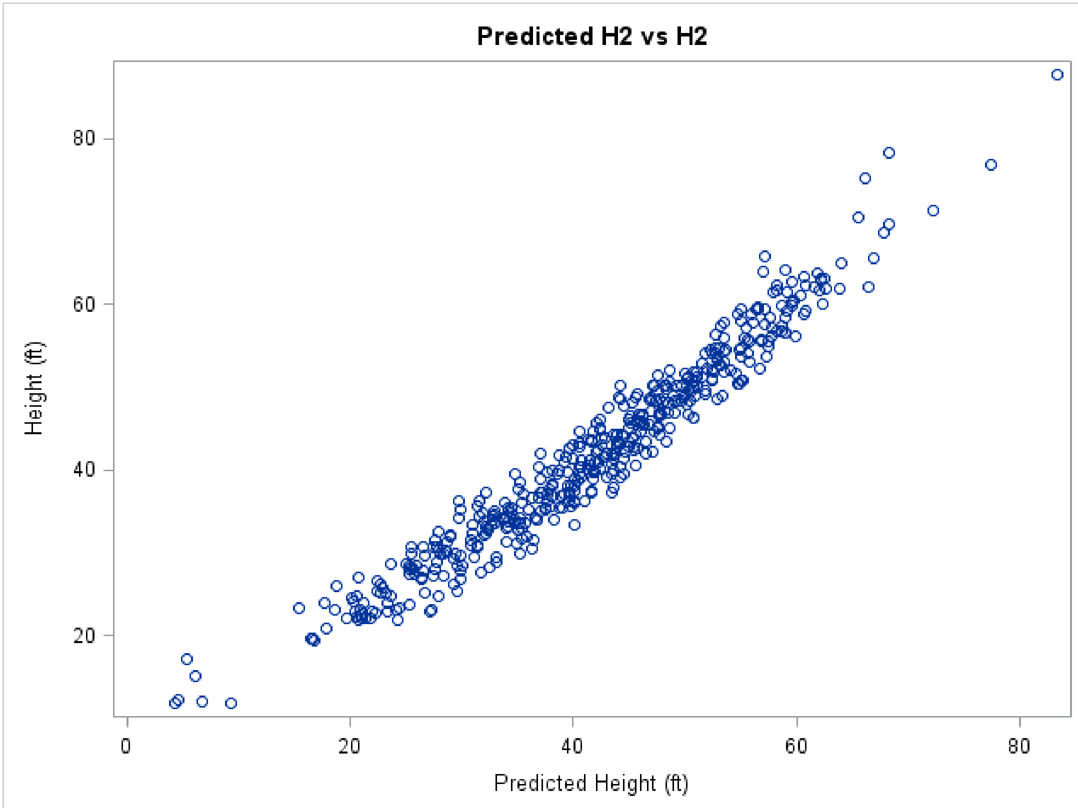

Figure 6. Plot of observed height against predicted height of trees from model [9].

Incorporating Soil/Climate Variables into Model

Incorporating key soil factors into the model

To find soil factors that had relatively more impacts on the model parameters, we first estimated the base model (equation 4) parameters (β_1 and β_2) by each plot, and these parameters were then correlated with plot soil variables. The calculated correlation coefficients (Appendix 4) indicated that percentages of carbon and nitrogen from soil profiles A and B (ACG, ANG, BCG, and BNG) had relatively strong correlations to β_1 parameter. On the other hand, percentages of carbon and nitrogen from profile B (BCG and BNG) had better correlations to parameter $\beta_2$than other variables.

These selected factors were incorporated into our selected Equation (6) in 2 different ways to express soil effects;

$$S_I = H\left[\frac{1-e^{-[(\beta_1 * t_I)+\beta_{1k}S_{1k}]}}{1-e^{-[(\beta_1 * t)+\beta_{1k}S_{1k}]}}\right]^{(\beta_2+u_2+\beta_{2k}S_{2k})} + e \qquad [10]$$

and

$$S_I = H\left[\frac{1-e^{-[(\beta_1)+\beta_{1k}S_{1k}]*(t_I)}}{1-e^{-[(\beta_1)+\beta_{1k}S_{1k}]*(t)}}\right]^{(\beta_2+u_2+\beta_{2k}S_{2k})} + e \qquad [11]$$

All other parameters remained the same. S_{1k} represents the variable ANG, ACG, BNG or BCG and S_{2k} represents the variable BCG or BNG for S_{2k}. The listed variables were respectively entered individually into model [10] and [11]; labelled [10a] and [11a], resulting in 12 models in total. Results are summarized in Table 8.

Table 8. Comparison statistics of fit after incorporating soil variables ANG, ACG, BNG and BCG for S_{1k} and variables BCG and BNG for S_{2k} individually into Models [10] and [11].

Model	S_{1k}	S_{2k}	β_{1k} estimate (significance)	β_{2k} estimate (significance)	R^2	RMSE	AIC
[10a]	ACG		0.0574	1.0439	0.95	2.74	2162.9
	ANG		0.0443	0.9282	0.96	2.60	2153.5
	BCG		0.0435	0.9249	0.96	2.67	2145.0
	BNG		0.0396	0.8956	0.96	2.62	2142.2
		BCG	0.0633	1.0379	0.95	2.82	2162.6
		BNG	0.0633	0.9418	0.95	2.83	2160.8
[11a]	ACG		0.0561	1.1004	0.95	2.81	2163.5
	ANG		0.0692	1.0989	0.95	2.82	2164.1
	BCG		0.0702	1.0997	0.95	2.82	2163.8
	BNG		0.0843	1.0999	0.95	2.83	2162.8
		BCG	0.0632	1.0379	0.95	2.82	2162.6
		BNG	0.0633	0.9418	0.95	2.83	2160.8

Note: ANG – Nitrogen level in A horizon, ACG – Carbon level in B horizon, BNG – Nitrogen level in B horizon, BCG – Carbon level in B horizon.

From Table 8, it can be noted that all the models obtained high R^2 (>=0.95) and small RMSE (<=2.83 ft). Overall, the models [11a] were poorer than models [10a] based on RMSE and AIC. In [10a], incorporating soil variables to β_1 was better than incorporating them to β_2. Model [10a] fitted with soil variable (BNG) had the lowest AIC value of 2142.2 and the second-lowest RMSE value of 2.62 ft.

Additionally, we fitted the same key soil variables ANG, ACG, BNG and BCG for S_{1k} and variables BCG and BNG for S_{2k} concurrently into model [10] and [11]; labeled [10b] and [11b], resulting in 16 models (Table 9). The model [11b] of (BCG & BCG) and (BCG & BNG) were especially poor, with R^2 values being around 0.75 & 0.70, indicating low prediction quality. The R^2 values of the other models were similar around 0.95. The AIC values from all models ranged from 2144.2 to as high as 2951.9, and once again model [10b] outputs were better than [11b] in terms of AIC. The models with the lowest AIC value (=2144.2) were the model [10b] of BNG & BCG and of BNG & BNG, these models also had the low RMSE (2.61 and 2.62ft) and high R^2 value of 0.96.

Table 9. Comparison of statistics of fit after incorporating soil variables ANG, ACG, BNG and BCG for S_{1k} and variables BCG and BNG for S_{2k} concurrently into Models [10] and [11].

Model	S_{1k}	S_{2k}	θ_{1k} estimate (significance)	θ_{2k} estimate (significance)	R^2	RMSE (ft)	AIC
[10b]	ACG	BCG	0.0588	1.0038	0.95	2.76	2163.7
	ACG	BNG	0.0594	0.9204	0.95	2.77	2162.1
	ANG	BCG	0.0448	0.8957	0.96	2.61	2154.8
	ANG	BNG	0.0454	0.8437	0.96	2.62	2154.1
	BCG	BCG	0.0419	0.9615	0.96	2.66	2145.6
	BCG	BNG	0.0429	0.9500	0.96	2.67	2146.8
	BNG	BCG	0.0396	0.8942	0.96	2.61	2144.2
	BNG	BNG	0.0398	0.8828	0.96	2.62	2144.2
[11b]	ACG	BCG	-0.0946	0.6833	0.96	2.69	2167.2
	ACG	BNG	-0.0932	0.6271	0.95	2.69	2166.3
	ANG	BCG	-0.1841	0.6877	0.95	2.66	2169.1
	ANG	BNG	-0.1577	0.6329	0.96	2.66	2168.2
	BCG	BCG	0.0433	-0.0296	0.75	6.37	2951.9
	BCG	BNG	0.0493	-0.2763	0.70	7.00	2888.7
	BNG	BCG	-0.5903	0.7129	0.95	2.68	2168.1
	BNG	BNG	-0.5316	0.6761	0.95	2.68	2167.8

Note: ANG – Nitrogen level in A horizon, ACG – Carbon level in B horizon, BNG – Nitrogen level in B horizon, BCG – Carbon level in B horizon.

Based on AIC and RMSE, model [10] fitted with soil variable (BNG) to adjust θ_1 was chosen and used in the final phase of factors incorporated into model. The model was as follows;

$$S_I = H\left[\frac{1-e^{-[(0.03957t_I)+0.155*BNG]}}{1-e^{-[(0.03957t)+0.155*BNG]}}\right]^{(0.8956+u_2)} + e \qquad [12]$$

Table 10. Itemized parameter estimates for model [12] with soil variable BNG.

Parameter	Estimate	Standard Error	t Value	Pr > |t|	95% Confidence Limits	
β_1	0.039	0.007	5.420	<.0001	0.025	0.054
β_2	0.896	0.036	24.760	<.0001	0.824	0.967
β_3	0.155	0.024	6.420	<.0001	0.107	0.203
s2e	7.603	0.592	12.850	<.0001	6.431	8.775
s2u	0.007	0.002	2.850	0.0052	0.002	0.011

This model was compared to model [8] and the result indicated that it is significantly better than model [8] (Table 11). The model precision (R^2) value of model [12] was higher compared to that of model [8]. The RMSE of model [12] was lesser than that of model [8], the AIC value was also lesser than model [8]. The log-likelihood ratio test also indicated that incorporating key soil factor into model improved the model.

Table 11. Fit statistics comparison of model [8] and model [12].

Model	R^2	Bias (ft)	RMSE (ft)	AIC	Log-likelihood ratio test p-value with base model
[8]	0.94	0.03	3.02	2374.4	
[12]	0.96	0.00	2.62	2142.2	<0.0001

The model residual figures (Figure 7) below showed that the model assumptions were much improved compared to those of the model [8] (Figure 3). The predicted height and observed height surround the diagonal line (Figure 8), suggesting the improved accuracy.

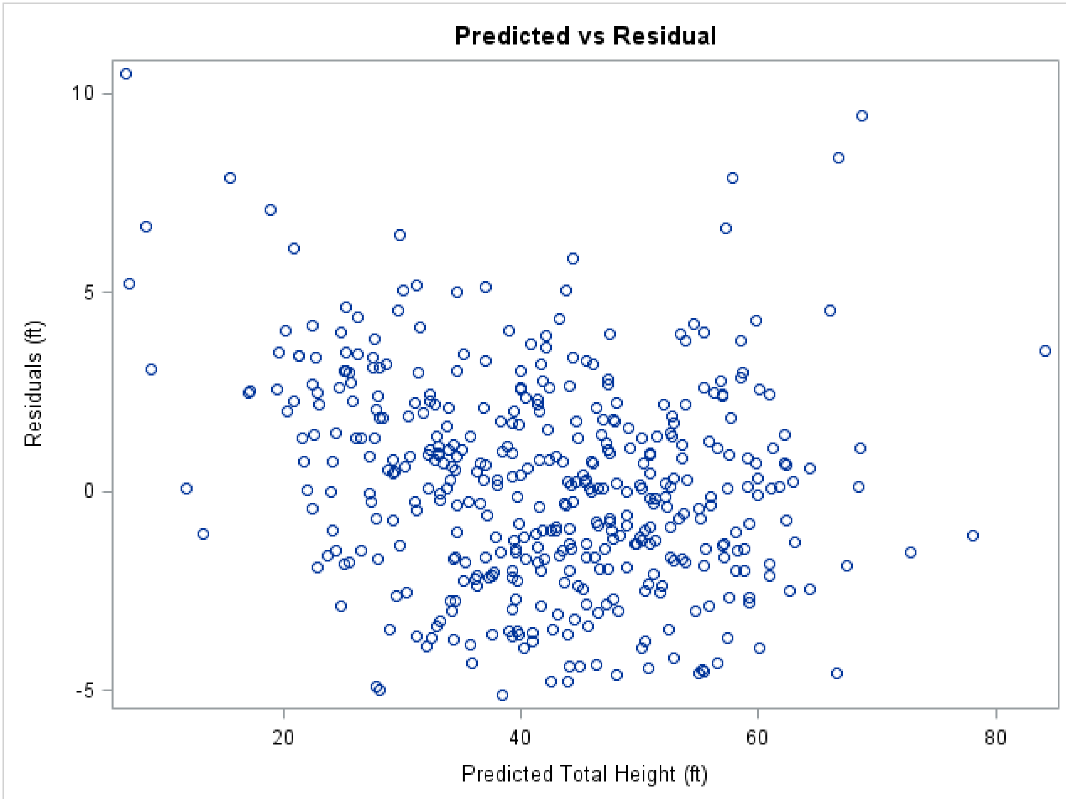

Figure 7. Plot of residuals against predicted height for soil variable model [12].

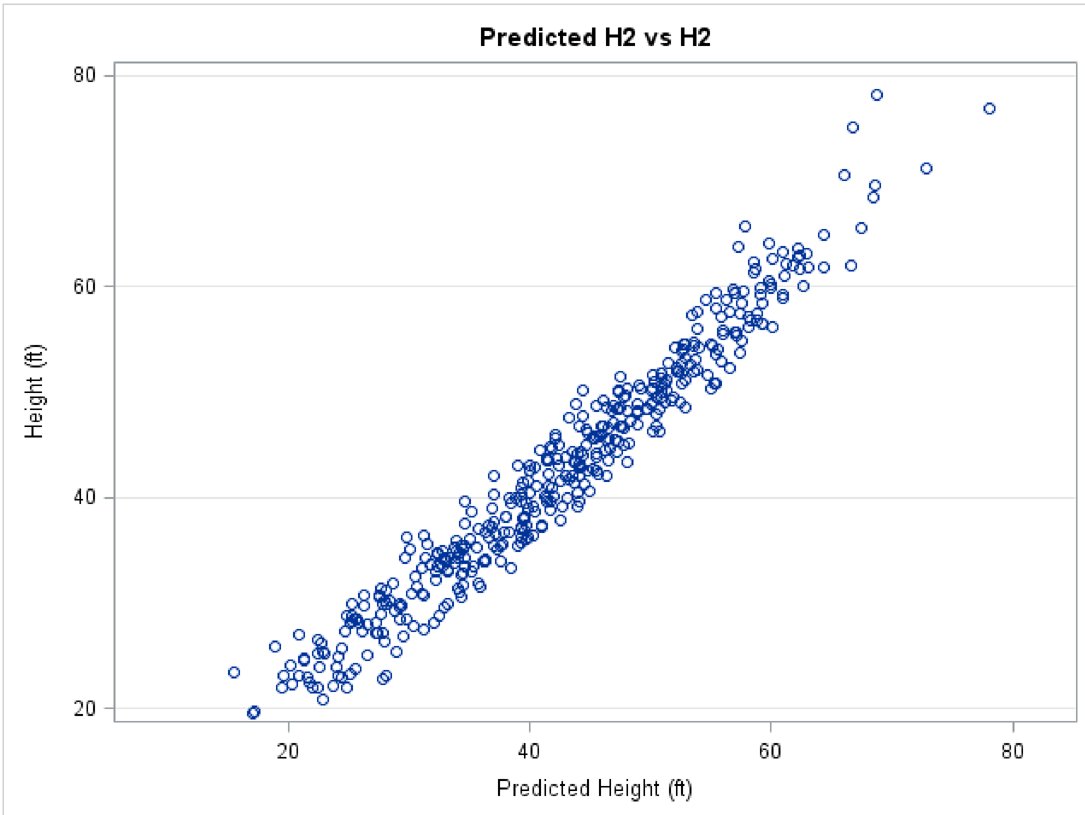

Figure 8. Plot of predicted height against total height of plantation for soil variable model [12].

Incorporating Key Climate Factors into Model

The correlation analysis indicated that both average winter and spring precipitation (mApct and mBpct) affected β_1 and β_2 (Appendix 5); while average summer max temperature, summer mean temperature and average fall precipitation (mCtmax, mCtmean & mDpct) which were all strongly correlated to mApct and mBpct affected parameter β_2. We began by fitting selected factors (mApct and mBpct) to express climate effect in 3 different form of Equation (6) expressed as;

$$S_I = H\left[\frac{1- e^{-\left[(\beta_1 * t_{A1}) + \beta_{1j}C_{1j}\right]}}{1- e^{-\left[(\beta_1 * t) + \beta_{1j}C_{1j}\right]}}\right]^{(\beta_2 + u_2)} \qquad [13]$$

$$S_I = H\left[\frac{1- e^{-\left[(\beta_1) + \beta_{1j}C_{1j}\right] * (t_{A1})}}{1- e^{-\left[(\beta_1) + \beta_{1j}C_{1}\right] * (t)}}\right]^{(\beta_2 + u_2)} \qquad [14]$$

and

$$S_I = H\left[\frac{1- e^{-[(\beta_1 * t_{A1})]}}{1- e^{-[(\beta_1 * t)]}}\right]^{(\beta_2 + u_2 + \beta_{2j}C_{2j})} \qquad [15]$$

Where C_{1j} represents the variables mApct or mBpct and C_{2j} represents the variable mApct or mBpct. These variables were entered individually into the above 3 models and labelled as [13a], [14a] and [15a]. The resulting parameters estimated and fit statistics from all 3 models fitted were summarized in Table 12 and compared.

Table 12. Fit statistics comparison of climate variables mApct and mBpct incorporated individually as C_{1j} and C_{2j} into models [13], [14] and [15].

Model	C_{1j}	C_{2j}	β_{1j} estimate (significance)	β_{2j} estimate (significance)	R^2	RMSE (ft)	AIC
[13a]	mApct		0.0392	0.8946	0.95	2.59	2358.3
	mBpct		0.0373	0.8812	0.96	2.57	2355.1
[14a]	mApct		0.0166	1.0997	0.95	2.57	2373.6
	mBpct		0.0333	1.1015	0.95	2.82	2374.2
[15a]		mApct	0.0620	1.6301	0.95	2.81	2370.7
		mBpct	0.0623	1.9115	0.95	2.81	2373.3

Overall all 3 models obtained high R^2 values of >=0.95 (Table 12). Evaluations from model [13a] had the lowest AIC values (2358.3 and 2355.1) and these model also had the low RMSE values of 2.59 and 2.57. The model with smallest RMSE and AIC values and preferably better prediction quality is considered. The model chosen was expressed as;

$$S_I = H\left[\frac{1-e^{-[(\beta_1 * t_I)+0.03725*mBpct]}}{1-e^{-[(\beta_1 * t)+0.03725*mBpct]}}\right]^{(\beta_2+u_2)} \quad [16]$$

All parameters remain the same. This model was compared to model [9] (Table 13)

Table 13: Statistics comparison between model [8] and model [16].

Model	R^2	Bias (ft)	RMSE (ft)	AIC	Log-likelihood ratio test p-value with model 16
[8]	0.94	0.03	3.02	2374.4	
[16]	0.96	0.00	2.57	2355.1	<0.0001

Model precision (R^2) value of model [16] was higher compared to that of model [8]. The RMSE of model [16] was lesser than that of model [8] as well the AIC value was also less than model [8] (Table 13). This result suggested that model [16] was significantly better than model [8]. The log-likelihood ratio test also indicated that incorporating key soil factor into model improved the model.

We fitted all other correlated factors (mApct, mBpct, mCtmax, mCtmean and mDpct) together in 2 different forms of the model as;

$$S_I = H\left[\frac{1- e^{-\left[(\beta_1 * t_I)+\beta_{1j}C_{1j}\right]}}{1- e^{-\left[(\beta_1 * t)+\beta_{1j}C_{1j}\right]}}\right]^{(\beta_2+u_2+\beta_{2j}C_{2j})} \quad [17]$$

and

$$S_I = H\left[\frac{1- e^{-\left[(\beta_1)+\beta_{1j}C_{1j}\right]*(t_I)}}{1- e^{-\left[(\beta_1)+\beta_{1j}C_1\right]*(t)}}\right]^{(\beta_2+u_2+\beta_{2j}C_{2j})} \quad [18]$$

Variables mApct or mBpct for C_{1j} and mApct, mBpct, mCtmax, mCtmean and mDpct for C_{2j} were fitted concurrently into model [17] and [18]; labelled as [17a] and [18a]. Table 14 shows comparison of the resulting 20 models.

Table 14. Fit statistics comparison of climate variables mApct or mBpct for C_{1j} and mApct, mBpct, mCtmax, mCtmean and mDpct for C_{2j} fitted concurrently into model [17] and [18].

Model	C_{1j}	C_{2j}	C_{1j} estimate (significance)	C_{2j} estimate (significance)	R^2	RMSE (ft)	AIC
[17a]	mApct	mApct	0.0375	1.4851	0.95	2.81	2354.3
	mApct	mBpct	0.0378	2.0687	0.95	2.81	2357.7
	mApct	mCtmax	0.1514	1.8008	0.95	2.81	2505.9
	mApct	mCtmean	0.1546	1.8962	0.95	2.81	2522.9
	mApct	mDpct	0.0381	1.6170	0.95	2.81	2345.7
	mBpct	mApct	0.0364	1.3943	0.95	2.57	2352.6
	mBpct	mBpct	0.0365	1.8436	0.95	2.56	2355.3
	mBpct	mCtmax	0.1547	1.8051	0.92	3.46	2508.6
	mBpct	mCtmean	0.1613	1.8733	0.92	3.51	2520.3
	mBpct	mDpct	0.0366	1.5669	0.96	2.58	2343.8
[18a]	mApct	mApct	0.2973	2.7100	0.95	2.77	2368.9
	mApct	mBpct	0.0619	1.9113	0.95	2.81	2375.3
	mApct	mCtmax	0.0809	-2.246	0.95	2.81	2365.9
	mApct	mCtmean	0.2538	1.8438	0.21	10.81	4761.5
	mApct	mDpct	0.1166	1.9654	0.95	2.84	2363.0
	mBpct	mApct	0.7910	2.6439	0.95	2.79	2366.5
	mBpct	mBpct	0.5803	4.2458	0.95	2.78	2373.2
	mBpct	mCtmax	0.1878	-2.3361	0.95	2.81	2365.5
	mBpct	mCtmean	0.5698	-14.617	0.95	2.79	2364.1
	mBpct	mDpct	0.2001	1.9118	0.95	2.85	2363.1

The R^2 values indicated variation in the quality of predictions which ranged from 0.21 to 0.96. The model [18a] of mApct and mCtmean had the lowest values with R^2 of 0.21 and the highest RMSE value of 10.81 ft. The R^2 values of other models were >=0.92. In terms of AIC values, it ranged from 2343.8 to 4761.5, and once again the model [18a] of mApct and mCtmean considered the poorest of all models had the highest value. Model [17a] with mBpct and mDpct had the lowest AIC value (2343.8) and low RMSE (2.58 ft). The model with the best statistical characteristics was chosen and expressed as;

$$S_I = H\left[\frac{1-e^{-[(0.03658*t_I)+0.006183*mBpct]}}{1-e^{-[(0.03658*t)+0.006183*mBpct]}}\right]^{(1.5669+u_2-0.1828*mDpct)} \quad [19]$$

Model [19] was compared to base model [8] (Table 15). There was clear difference in their respective inferential statistic values. Model [19] had better prediction quality in the R^2 value, as well as the measure of accuracy in RMSE value. The AIC value of model [19] was also lower than that of model [8]. The log-likelihood ratio test proved significant difference in model [19] compared to model [8].

Table 15. Fit statistics comparison between model [8] and model [19]

Model	R^2	Bias (ft)	RMSE (ft)	AIC	Log-likelihood ratio test p-value with base model
[8]	0.94	0.03	3.02	2374.4	
[19]	0.96	0.00	2.58	2343.8	<0.0001

However, we compared model [19] with model [16] (Table 16). Both models displayed significant RMSE values as well as good prediction quality. The clear difference distinguishing both models was found in their AIC values with model 16d of mBpct and mDpct having the lowest value (=2343.8). This outcome indicated that increment in the number of parameter almost always improves the goodness of fit of a model. The log-likelihood ratio test proved significant difference in model [19] compared to model [16].

Table 16. Fit statistics comparison between model [16] and [19].

Model	R^2	BIAS	RMSE	AIC	Log-likelihood ratio test p-value with model 16c
[16]	0.96	0.00	2.57	2355.1	
[19]	0.96	0.00	2.58	2343.8	<0.0001

Overall the model [19] was considered best fit and kept to be used for final evaluation processes. Model [19] residual figures as shown below illustrates the model assumptions such as normality, independence and equal variance are well acceptable (Figure 9). The plot of predicted height of model [19] against observed height showed better consistency, as it tends to cluster even more in the diagonal line (Figure 10).

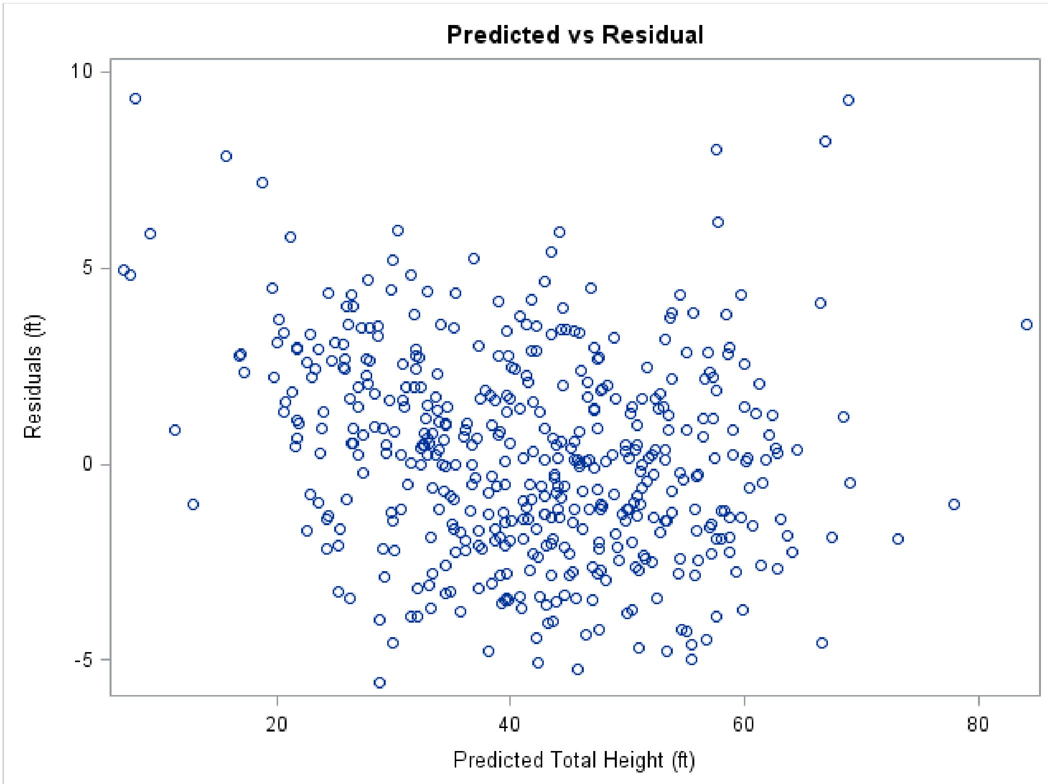

Figure 9. Plot of residuals against predicted height for climate variable selected model [19].

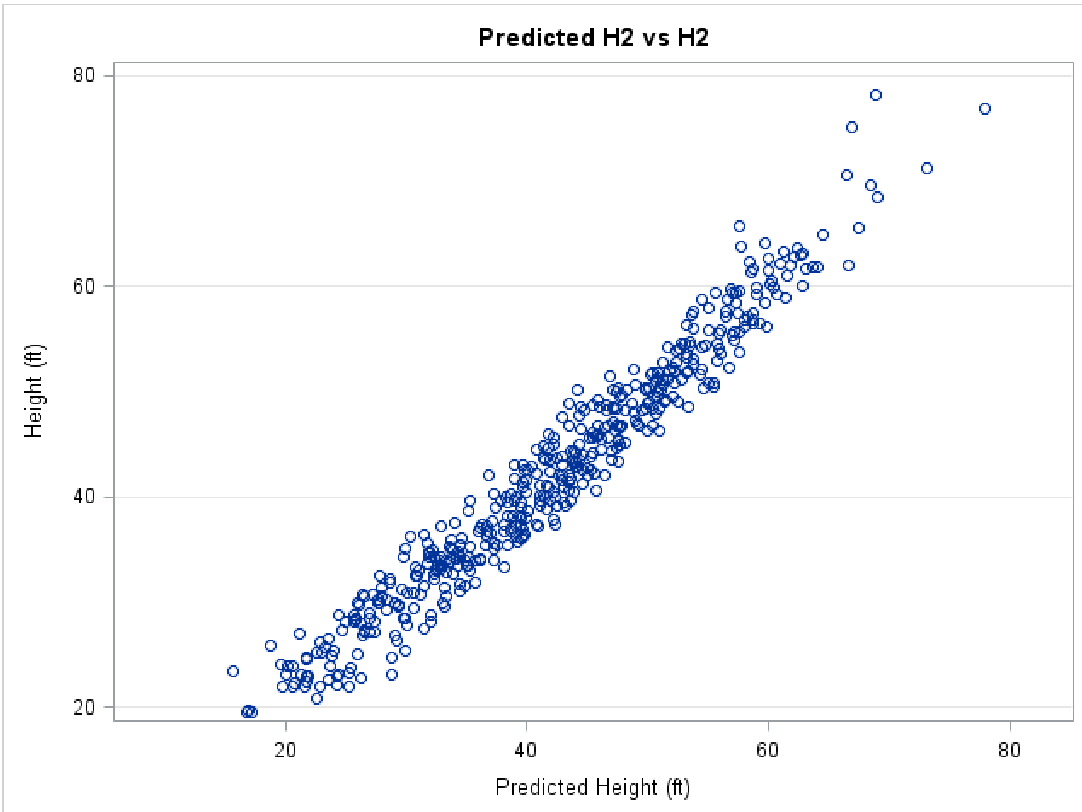

Figure 10. Plot of predicted height against total height of trees for climate variable selected model [19].

Incorporating Both Climate and Soil Variable

All initial procedures and model fitting were carried out to choose the best and appropriate variables and model to be considered for final evaluation. Total nitrogen content (of soil) in the B horizon, average spring mean precipitation (mBpct) and average fall mean precipitation (mDpct) variables matched as best suited fit. These variables and the height-age data were used in combined form and fitted into equation (6) expressed as;

$$S_I = H\left[\frac{1-e^{-\left[(\beta_1 * t_I)+\beta_{1j}C_{1j}+\beta_{1k}S_{1k}\right]}}{1-e^{-\left[(\beta_1 * t)+\beta_{1j}C_{1j}+\beta_{1k}S_{1k}\right]}}\right]^{\left(\beta_2+u_2+\beta_{2j}C_{2j}\right)} + e \qquad [20]$$

Where BNG for S_{1k}, mBpct for C_{1j} and mDpct for C_{2j} respectively. Using similar procedures, all initial parameter values were set followed by successive iteration until convergence criterion attained. The final model was expressed as;

$$S_I =$$

$$H\left[\frac{1-e^{-[(0.04066 * t_I)+0.1511 * mBpct+0.000175 * BNG]}}{1-e^{-[(0.04066 * t)+0.1511 * mBpct+0.000175 * BNG]}}\right]^{(1.6681+u_2-(0.2026 * mDpct))}$$

[21]

We compared this final model [21], with model [8] (Table 17). Model [21] had R^2 value of 0.96, a RMSE value of 2.64, and a much lower AIC value of

2132.5. Statistically, model [21] had better outcome than model [8]. The log-likelihood ratio test also proved significance in model comparison.

Table 17. Fit statistics comparison between model [8] and model [21]

Model	C_{1j} & S_{1k}	C_{2j} & S_{2k}	R^2	BIAS	RMSE	AIC	Log-likelihood ratio test p-value
[8]	.	.	0.94	0.03	3.02	2374.4	
[21]	BNG, mBpct	mDpct	0.96	0.00	2.64	2132.5	<0.0001

However, we compared model [21] with the selected soil model [12] (Table 18). The R^2 values of both models were similar in 0.96. Model [12] had slightly better model accuracy in RMSE but model [21] had better AIC value interpretation (lowest value). The log-likelihood ratio test indicates improvement in the model as well.

Table 18. Fit statistical comparison between model [12] and model [21]

Model	C_{1j} & S_{1k}	C_{2j} & S_{2k}	R^2	BIAS	RMSE	AIC	Log-likelihood ratio test p-value
[12]	BNG	.	0.96	0.00	2.62	2142.2	
[21]	BNG, mBpct	mDpct	0.96	0.00	2.64	2132.5	<0.0001

Likewise, we compared model [21] with the selected climate model [19] (Table 19). The log-likelihood ratio test showed improvement but the model accuracy of model [21] had a higher value of 2.64 ft compared that of model [19] being (=2.58 ft). The R^2 values of both models were similar in 0.96. The AIC value estimated from model [21] was lower compared to model [19].

Table 19. Fit statistical comparison between model [19] and model [21]

Model	C_{1j} & S_{1k}	C_{2j} & S_{2k}	R^2	BIAS	RMSE	AIC	Log-likelihood ratio test p-value
[19]	mBpct	mDpct	0.96	0.00	2.59	2343.8	
[21]	BNG, mBpct	mDpct	0.96	0.00	2.64	2132.5	<0.0001

The model residuals indicated that the model assumptions were not violated (Figure 11). The model predicted height well at both low and high ends of the data range and also those of the middle range (Figure 12). The predicted height of model [21] showed consistency as data tend to cluster tightly in the diagonal.

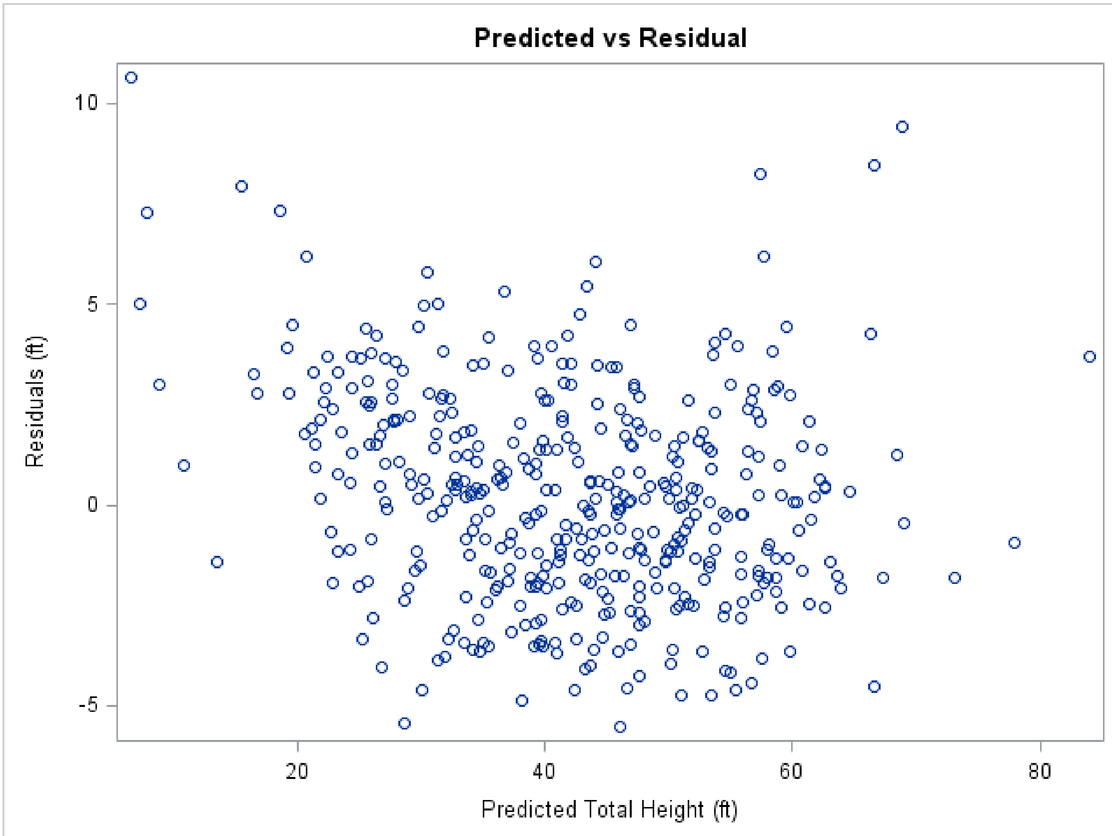

Figure 11. Plot of residuals against predicted height for soil and climate variables selected model [21].

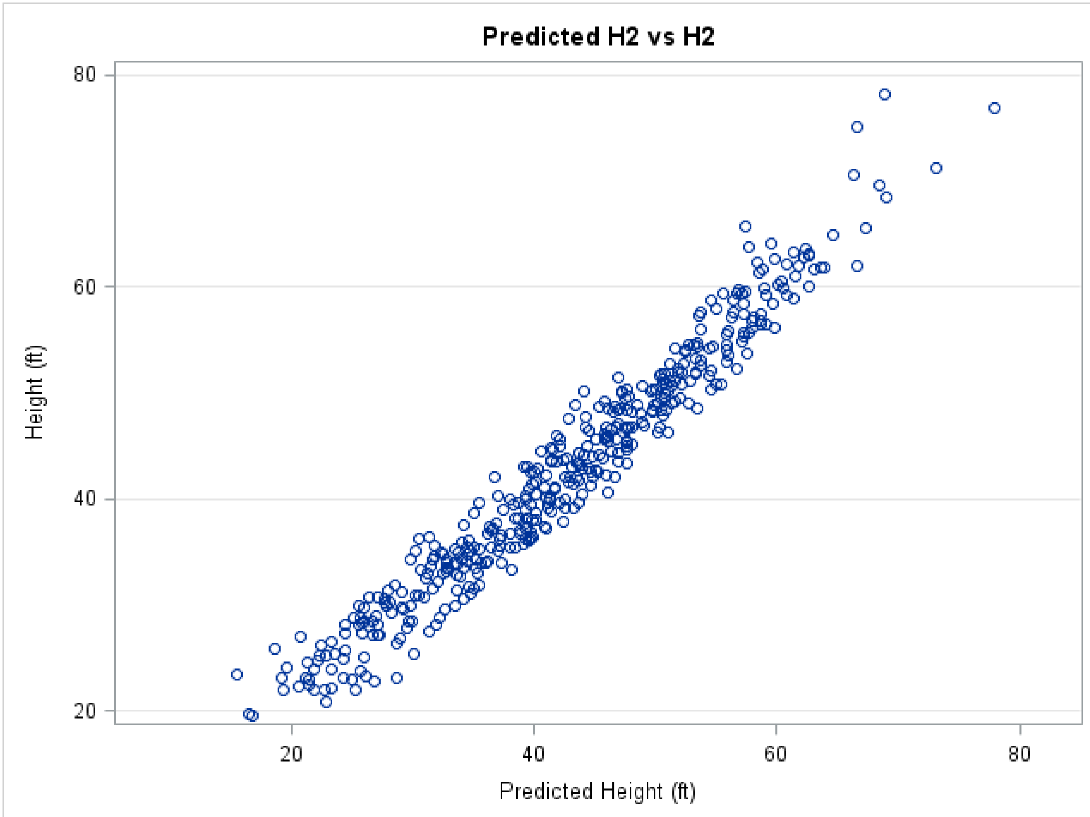

Figure 12. Plot of predicted height against total height of plantation for soil and climate variables selected model [21].

Effects of Soil/Climate changes on Height growth

Soil

In order to examine the effect of the changes in soil on the predicted tree height growth of plantation, we simulated the key selected soil variables using Model [12]. The mean value of BNG from all plots was estimated as 0.14ppm, with a minimum of 0.07ppm, and maximum of 0.28ppm. Total tree height was plotted against plantation age displaying the changes in tree height with changes in the soil variable across plantation age. (Figure 13).

Results from the estimation showed that effect of BNG was positive and hence tree height is directly proportional to change in BNG. At given plantation age, tree height increased even greater as BNG increases. This indicated that soil factor (BNG) had significant effect on the height growth of loblolly pine tree.

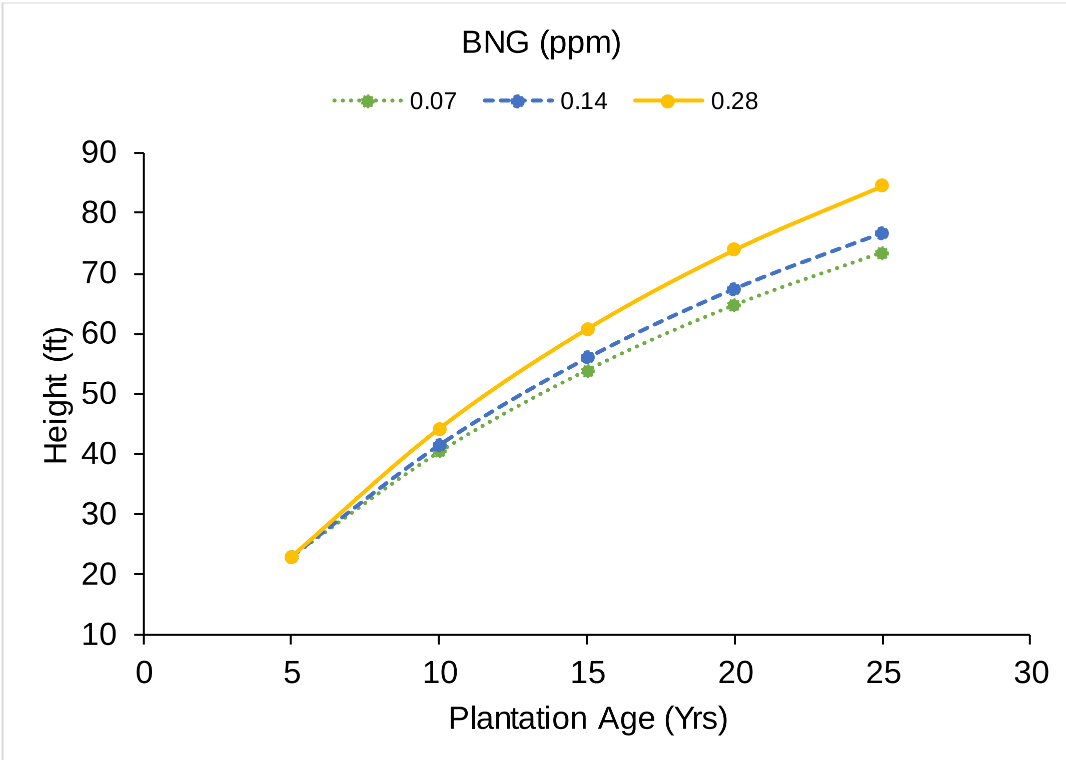

Figure 13. Effect of BNG changes on tree height growth of loblolly pine.

Climate

As an illustration to demonstrate the effect of changes in climate conditions on predicted tree height of loblolly pine we developed growth curves using Model [19]. To do this, we varied one climate variable but fixed the other variable as a constant (the average). In the simulation, mDpct was first replaced with the mean value from 2000 to 2017 and the targeted variable (mBpct) was taken as 2.58mm day^{-1}, 3.58mm day^{-1} and 4.58mm day^{-1} respectively. Then we replaced mBpct with the mean value from 2000 to 2017 and the targeted variable (mDpct) was taken as 2.77mm day^{-1}, 3.77mm day^{-1} and 4.77mm day^{-1} respectively. Total tree height was plotted against plantation age displaying the changes in total height with changes in the soil variable across plantation age. (Figure 14A and 14B).

The change in both climate factors directly affected tree height. Although there was increase in tree height with given plantation age but change in mBpct had positive changes in tree height (Figure 14A). On the other hand, the significant difference in predicted height observed from the change in mDpct was reverse. Loblolly pine tree height was inversely proportion to change in mDpct hence tree height tend to reduce with increase in fall precipitation (Figure 14B). This indicated that climate factor mDpct had more effect on tree height than mBpct.

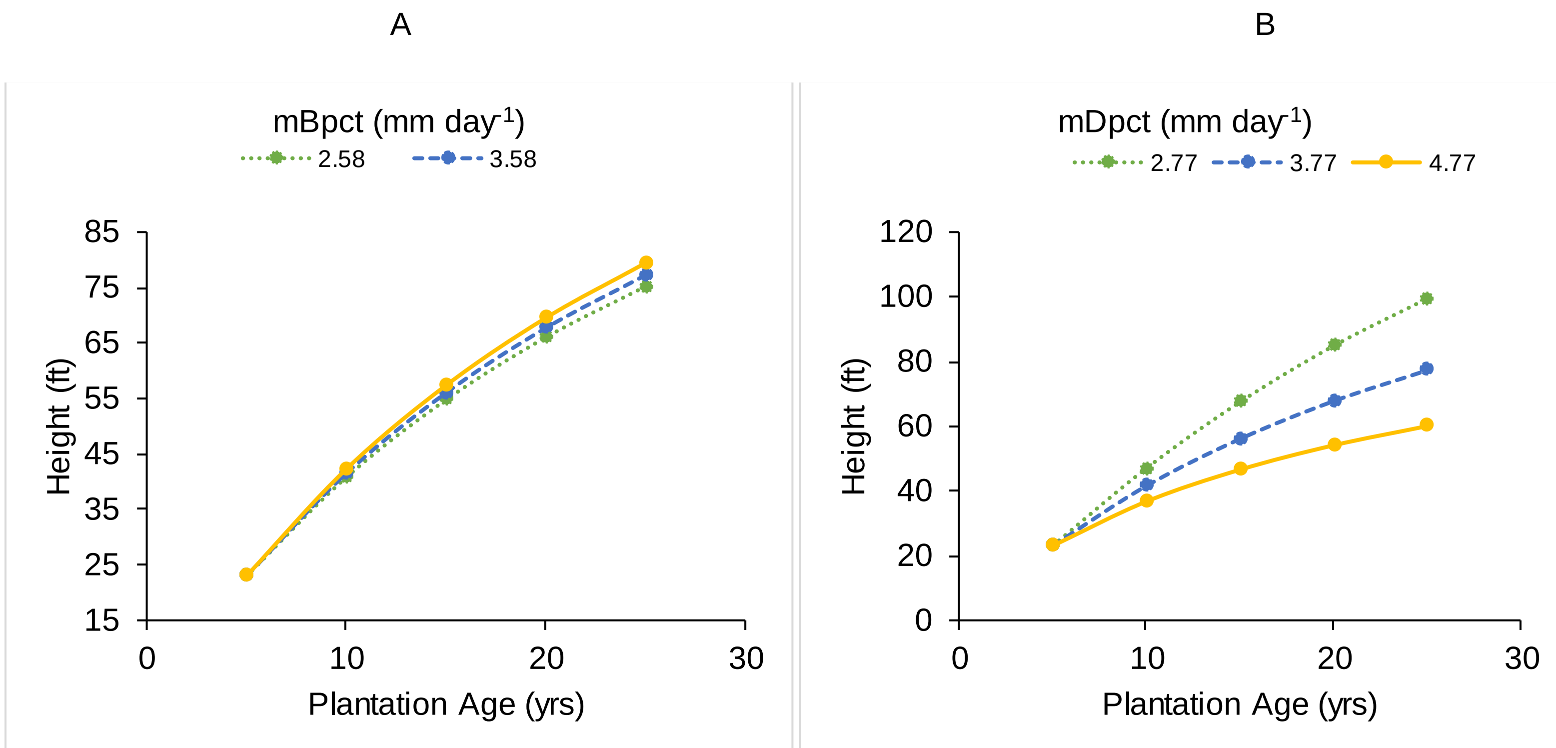

Figure 14. Effect of climate on predicted height of loblolly pine. Subplot a and b represent changes in tree height growth with mBpct and mDpct respectively. (a) mBpct = 2.58mm day^{-1}, 3.58mm day^{-1}, 4.58mm day^{-1}; mDpct = 3.77mm day^{-1}; (b) mBpct = 3.58mm day^{-1}; mDpct = 2.77mm day^{-1}, 3.77mm day^{-1} and 4.77mm day^{-1}.

DISCUSSION

This study identified important soil and climate variables affecting the height-age relationship for loblolly pine plantations in east Texas. Multiple studies have been conducted to understand the influence of climate and soil on height growth (Aguilar 1979; Chang and Aguilar 1980; Brown 1994; Fontes et al. 2003; Amateis et al. 2006; Monserud et al. 2008; Beer 2009; Weiskittel et al. 2011a, b; Burkhart and Tome 2012; Sabatia and Burkhart 2014; Sharma et al. 2015; Farjat et al. 2015; Subedi and Fox 2016).

Among all the soil variables investigated, the key variable identified in this study was the nitrogen level of horizon B for soil. The nitrogen level of in B horizon had significant effect on the height of loblolly pine trees. The height growth improves with increasing soil nitrogen levels in B horizon (Figure 13). Similar to our study, in Subedi and Fox (2016) study, total nitrogen was one of the five soil properties selected as significant predictor variables, considered to be a limiting nutrient in loblolly pine plantations. A study by Allen et al. (1990) indicated that low soil nutrient availability contributed to reduced productivity of southern pine and nitrogen was observed as one of the key nutrients, also this was seen in our study from the effect of BNG of height (Figure 13). There were similar findings in a study by Fox et al. (2007), and from their observation, increasing nitrogen would increase the available soil nutrient and thus increase height growth. The effect soil variables pose on the height growth of loblolly pine is considered significant.

Among all the climate variables investigated, the key variables were average precipitation in spring and fall seasons and affected the height growth of loblolly pine trees. The height growth improved with increasing spring season precipitation but showed a down curve with increasing precipitation for the fall season (Figure 14). Both temperature and precipitation were used in our analysis to assess their impact on the SI model and identify the key factor influencing the SI of plantation loblolly pine. The variables identified as key predictor variables was used and hence other variables did not affect height growth in this study. One reason for the insignificant effect of temperature in this study is attributed to the differences in temperature from the plot to plot were not substantial. Previous studies also supported our findings. In Brown's (1994) study, he observed total spring precipitation as one of the weather parameters that influence height growth. In a similar study by Sharma et al. (2015), one of the climate variables that had a significant effect on tree height of Jack Pine specie was precipitation.

Elsewhere, Sabatia and Burkhart 2014), also identified annual precipitation as an important biophysical variable considered in loblolly pine SI models. Beer's (2009) reported precipitation (considered as rainfall) had a significant effect on tree growth and this was because the amount of rainfall tends to increase the available water capacity in the soil.

SI models are sensitive to silvicultural practices and in most cases the resulting predicted tree quality from modeling procedures indicate improvement as regards the type of management system that was applied to the respective plantation (Zhang et al. 1997; Fontes et al. 2003; Sharma et al. 2006; Weiskittel et al. 2011a, b; Zhao et al. 2016). More recently, Trim et al. (2020) developed two SI models (Chapman – Richards GADA and McDill Amateis GADA model) for the intensively-managed plantations in east Texas and found their models predicted greater height growth than the Lenhart (1986) and Coble and Lee (2010). They ascribed this to the change of management level from extensive to intensive on the plantations. While the intensive silvicultural management may be one major reason for greater predicted height, their study never accounted for other factors that could influence the growth rate.

In many forest researches, using on-line soil data is becoming popular, even though the accuracy of these on-line soil data is largely unknown. One topic of this study was to compare observed and corresponding on-line soil data in soil texture in East Texas and western Louisiana. Most of the chemical test values for horizon A had larger values than those of horizon B. This is an expected result since A horizon is somewhat considered the surface horizon and it serves as a pathway for materials and minerals to move down in a soil profile. Most chemical components and minerals are leached down and accumulated in the B horizon and this would occur over certain period of time. While most plots had the same identification of texture, some inconsistencies existed in some plots, in particular the B horizon. The exact reason for this inconsistency was unknown but likely may be contributed by a few factors. For one, the method of data collection and compilation would differ and the location (point) of collecting individual soil data would also vary. In most cases, soil data from online sources are derived via a means of extrapolation of data as well as the scaling system used for the data across each region. This method doesn't estimate the exact point of soil extraction. Nonetheless, our results do suggest that precaution should be taken when on-line soil texture data are used in forest research in East Texas and Western Louisiana.

Ideally, the model of this study should be tested using an independent dataset, or, alternatively, data can be split with one part for model development and the other for model verification. Neither was done in this study for one the dataset was relatively small, only about 400 observations, and one of our goals was to identify key soil/climate variables affecting height-age relationships. Our model selection was based on the typical statistical model comparison method of comparing AIC and applying the log-likelihood ratio test when two models are nested to each other. The significant improvement in AIC by comparing models incorporating soil and/or climate variables to the base model (Tables 11, 15, 17) suggests that incorporating these variables could improve the model predictability. Also their residual plots had no clear pattern or trend.

The roles biophysical factors play in the growth of pine trees are crucial in forest management. With this knowledge, we can improve and implement more silvicultural practices in loblolly pine plantations. As an essential soil nutrient needed for growth, increasing the nitrogen level (preferably in B horizon) would enrich the soil and be of great advantage as this should increase productivity.

CONCLUSION

In assessing the effect of environmental variables on the growth potential of pine plantations, we observed that there is a strong relationship between tree growth and soil/climate variables.

The nitrogen level in B soil horizon was the one soil factor that significantly affected tree height growth. It indicated that an increase in this soil variable would yield tree height growth. Being it one of the limiting soil nutrients, it is clear that nitrogen is an essential soil nutrient needed in a growing tree. Precipitation (spring and fall) was the climate factors that significantly affected tree height growth. This factor varied seasonally and would affect the available water in the soil. Incorporating both climate and soil parameters into the model improved the model performance. Our models have indicated a reduction in the bias of the variables to consider when predicting SI to evaluate the quality of pine plantations. The models should continuously be modified when more data become available.

LIMITATIONS

The limitations of this study were;

- Accessibility to some plots was limited due to property restrictions by owner/management. Plantation plots under the ETPPRP Phase II are owned by different organizations/companies, as so, some plots location have rigid restriction policies to reduce theft and unwanted farmland activities.
- In retrieving climate data, careful evaluation and extraction procedures should be used because such data varies across platforms and different measured values are found for individual climate variables. The climate data had slightly different or the same values due to the proximity of some plot locations being so close.
- From our data, the age range of the plantation used in the study indicated this plantation is young. Evaluating data older than 22 years which was the maximum age was done by extrapolation.

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APPENDIX

Table 1. Observations from physical and chemical properties test of ETPPRP Phase II plots.

PLOT	PROFILE	HORIZON/DEPTH RANGE	SAND (%)	CLAY (%)	SILT (%)	TEXTURAL CLASS	NH4 (ppm)	C (%)	N (%)
200	A	0 - 11"	77.56	7.54	14.90	Sandy Loam	7.347	1.429	0.149
	B	11"+	58.65	28.44	12.90	Sandy Clay Loam	6.92	0.889	0.146
201	A	0 - 7.5"	86.64	6.98	6.38	Loamy Sand	ND	1.293	0.151
	B	7.5"+	84.74	7.94	7.32	Sandy Clay loam	2.412	1.639	0.17
202	A								
	B								
203	A	0 - 6"	85.42	8.08	6.50	Sandy Loam	5.366	1.452	0.16
	B	6"+	71.70	15.94	12.36	Sandy Loam	ND	1.112	0.146
204	A								
	B								
205	A	0 - 9"	85.46	4.82	9.77	Sandy Loam	0.443	1.152	0.141
	B	9"+	77.78	17.72	4.50	Sandy Loam	0.197	0.936	0.147
206	A	0 - 7.5"	86.84	6.30	6.86	Loamy Sand	3.889	1.183	0.137
	B	7.5"+	84.54	6.70	8.76	Sandy Clay loam	ND	0.831	0.124
207	A	0 - 17.25"	79.48	11.34	9.18	Loamy sand	ND	1.1	0.134
	B	17.25"+	84.20	12.44	3.36	Sandy Clay loam	ND	0.752	0.116
208	A	0 - 5"	72.48	11.08	16.44	Loamy Sand	8.812	2.437	0.203
	B	5"+	64.30	18.08	17.62	Sandy Clay loam	3.151	0.843	0.142
209	A	0 - 17"	71.84	3.72	24.44	Sandy Loam	0.197	1.515	0.159
	B	17"+	66.88	6.72	26.48	Sandy Loam	ND	0.758	0.122
210	A	0 - 13"	76.50	6.22	17.32	Sandy Loam	1.674	1.599	0.16
	B	13"+	70.74	8.08	21.18	Loam	ND	0.716	0.126
211	A	0 - 10.25"	62.28	9.62	28.10	Sandy Loam	0.936	2.297	0.141
	B	10.25"+	52.02	13.72	34.26	Loam	ND	0.961	0.136
212	A								
	B								
213	A	0 - 7.00"	68.86	11.26	19.88	Silt Loam	6.35	1.435	0.167
	B	7.00"+	59.74	22.26	18.00	Silt Loam	0.197	1.009	0.169

Table 1. Observations from physical and chemical properties test of ETPPRP Phase II plots.

PLOT	PROFILE	HORIZON/DEPTH RANGE	SAND (%)	CLAY (%)	SILT (%)	TEXTURAL CLASS	NH4 (ppm)	C (%)	N (%)
214	A								
	B								
215	A	0 - 7.5"	56.74	6.32	36.94	Silt Loam	3.643	2.683	0.251
	B	7.5"+	49.78	14.40	35.82	Silt Loam	2.905	1.02	0.159
216	A	0 - 17.25"	79.28	5.36	15.36	Sandy Loam	ND	1.08	0.135
	B	17.25"+	65.56	15.26	19.18	Sandy Loam	0.197	0.71	0.133
217	A	0 - 11"	68.46	10.62	20.92	Sandy Loam	4.135	1.86	0.164
	B	11"+	44.50	21.58	33.92	Loam	0.443	0.758	0.148
218	A	0 - 14.00"	63.70	17.26	19.04	Sandy loam	4.381	1.633	0.168
	B	14.00"+	46.26	31.34	22.40	Clay loam	4.627	0.842	0.141
219	A	0 - 10.00"	50.92	26.62	22.46	Sandy Loam	6.492	1.381	0.174
	B	10.00"+	45.78	40.64	13.58	Clay	7.561	1.289	0.174
220	A	0 - 14.00"	57.44	23.30	19.26	Clay Loam	3.182	1.703	0.248
	B	14.00"+	46.74	25.08	28.18	Sandy Clay loam	2.455	0.977	0.165
221	A	0 - 14.00"	56.60	15.50	27.90	Sandy Loam	4.455	1.685	0.201
	B	14.00"+	52.28	18.62	29.10	Sandy Loam	2.636	0.939	0.159
222	A	0 - 7.00"	65.70	5.72	28.58	Silt Loam	3.182	1.497	0.159
	B	7.00"+	63.56	8.76	24.68	Silty Clay	2.273	0.774	0.114
223	A	0 - 9"	72.70	4.58	22.72	Sandy Loam	2.818	1.079	0.147
	B	9"+	68.92	11.50	19.58	Loam	2.091	0.808	0.145
224	A	0 - 14.00"	61.74	5.36	32.90	Sandy Loam	3.182	0.841	0.136
	B	14.00"+	56.60	6.36	37.04	Sandy Clay loam	2.273	0.682	0.108
225	A								
	B								
226	A								
	B								
227	A	0 - 10.00"	48.74	24.50	26.76	Sandy Clay Loam	7.775	2.222	0.213
	B	10.00"+	39.50	43.58	16.92	Clay	10.55	1.604	0.211

Table 1. Observations from physical and chemical properties test of ETPPRP Phase II plots.

PLOT	PROFILE	HORIZON/DEPTH RANGE	SAND (%)	CLAY (%)	SILT (%)	TEXTURAL CLASS	NH4 (ppm)	C (%)	N (%)
228	A	0 - 9"	88.84	3.82	7.34	Loamy Sand	3.173	1.02	0.148
	B	9"+	73.56	9.72	18.96	Sandy Loam	3.008	0.769	0.13
229	A	0 - 11"	72.42	7.90	19.68	Loamy Sand	3.173	1.953	0.193
	B	11"+	73.94	10.40	15.66	Clay	2.844	0.939	0.138
230	A	0 - 9"	51.92	30.72	17.36	Sandy Loam	10.13	3.729	0.298
	B	9"+	44.34	40.26	15.40	Clay	9.699	2.124	0.214
231	A	0 - 9"	83.20	4.94	11.86	Sandy Loam	5.851	1.483	0.164
	B	9"+	80.20	10.94	8.86	Sandy Clay loam	6.065	0.965	0.142
232	A	0 - 4.25"	82.90	12.04	5.06	Sandy Loam	3.643	1.709	0.173
	B	4.25"+	60.82	36.10	3.08	Silty Clay	2.166	1.155	0.168
233	A	0 - 10.00"	83.70	5.98	10.32	Loamy Sand	ND	1.355	0.145
	B	10.00"+	81.60	7.00	11.40	Loamy Sand	ND	0.688	0.117
234	A	0 - 11.50"	75.18	12.68	12.14	Loamy sand	3.397	1.589	0.168
	B	11.50"+	75.02	11.72	13.26	Loamy sand	ND	0.821	0.127
235	A	0 - 9"	74.66	20.62	4.72	Sandy Loam	2.636	1.631	0.177
	B	9"+	46.06	34.76	19.18	Clay	3.182	1.712	0.181
236	A	0 - 11"	86.70	5.80	7.50	Loamy Sand	2.844	1.053	0.129
	B	11"+	84.00	4.72	11.28	Loamy Sand	2.515	0.479	0.093
237	A	0 - 11"	82.48	11.44	6.08	Sandy Loam	4.782	1.896	0.203
	B	11"+	73.06	17.18	9.76	Sandy Clay Loam	3.927	0.915	0.149
238	A								
	B								
239	A	0 - 11.50"	74.28	5.68	20.04	Loamy sand	5.637	0.793	0.132
	B	11.50"+	64.28	7.68	28.04	Loamy Sand	5.432	0.625	0.121
240	A	0 - 9"	80.60	7.08	12.32	Loamy Sand	2.455	1.527	0.164
	B	9"+	66.56	25.08	8.36	Sandy Clay Loam	1.909	0.754	0.14
241	A	0 - 9"	71.56	10.90	17.54	Sandy Loam	4.455	1.498	0.164
	B	9"+	62.30	8.98	28.72	Loam	2.091	1.18	0.116

Table 1. Observations from physical and chemical properties test of ETPPRP Phase II plots.

PLOT	PROFILE	HORIZON/DEPTH RANGE	SAND (%)	CLAY (%)	SILT (%)	TEXTURAL CLASS	NH4 (ppm)	C (%)	N (%)
242	A	0 - 11"	86.70	5.94	7.36	Sandy Loam	5.637	0.872	0.138
	B	11"+	81.74	5.90	12.36	Clay	4.996	0.661	0.12
243	A								
	B								
244	A	0 - 4.50"	52.10	21.72	26.18	Loam	3.151	2.49	0.236
	B	4.50"+	56.14	14.72	29.14	Sandy Clay Loam	1.428	1.058	0.171
245	A	0 - 20.75"	85.66	4.82	9.52	Loamy Sand	ND	0.562	0.106
	B	20.75"+	85.64	4.82	9.54	Sandy Clay loam	ND	0.56	0.105
246	A								
	B								
247	A	0 - 13.3"	55.60	28.86	15.54	Sandy Loam	4.381	0.559	0.112
	B	13.3"+	44.70	44.86	10.44	Clay	5.12	0.559	0.117
248	A	0 - 13"	87.54	3.50	8.96	Sand	1.674	1.763	0.188
	B	13"+	89.38	2.58	8.04	Sand	ND	1.151	0.136
249	A	0 - 8.5"	85.38	4.68	9.94	Loamy Sand	3.727	1.153	0.114
	B	8.5"+	84.06	5.80	10.14	Sandy Clay loam	1.182	0.711	0.113
250	A	0 - 8.5"	60.44	12.86	26.70	Silt Loam	4.091	1.739	0.159
	B	8.5"+	48.66	22.72	28.62	Clay	1.909	0.884	0.13
251	A	0 - 11.50"	65.92	11.04	23.04	Silt Loam	1.545	1.389	0.144
	B	11.50"+	50.74	29.12	20.14	Clay	0.155	0.707	0.123
252	A	0 - 11.50"	72.20	10.72	17.08	Sandy Loam	6.455	1.769	0.14
	B	11.50"+	55.10	15.84	29.06	Loam	1.909	0.888	0.121
253	A	0 - 8.5"	69.30	10.72	19.98	Sandy Loam	2.091	1.064	0.132
	B	8.5"+	54.20	10.72	35.08	Clay Loam	1.364	0.812	0.121
254	A								
	B								
255	A	0 - 8.5"	71.48	9.86	18.66	Sandy Loam	4.273	1.835	0.193
	B	8.5"+	54.50	29.44	16.06	Clay	1.909	1.146	0.153

Table 1. Observations from physical and chemical properties test of ETPPRP Phase II plots.

PLOT	PROFILE	HORIZON/DEPTH RANGE	SAND (%)	CLAY (%)	SILT (%)	TEXTURAL CLASS	NH4 (ppm)	C (%)	N (%)
256	A	0 - 8.5"	71.92	12.72	15.36	Sandy Loam	2.455	1.642	0.153
	B	8.5"+	61.34	31.08	7.85	Sandy Clay Loam	1.909	0.878	0.138
257	A								
	B								
258	A	0 - 8.5"	78.12	9.44	12.44	Loamy Sand	2.091	1.767	0.182
	B	8.5"+	60.66	12.86	26.48	Sandy loam	1.545	0.984	0.133
259	A								
	B								
260	A	0 - 8.5"	73.42	11.08	15.52	Sandy Loam	2.844	1.265	0.149
	B	8.5"+	62.38	19.08	18.34	Clay	3.008	0.8	0.115
261	A	0 - 8.5"	86.70	10.00	3.30	Loamy Sand	2.515	1.11	0.147
	B	8.5"+	82.66	11.00	6.34	Sand Clay Loam	2.679	0.952	0.144
262	A	0 - 15.50"	41.56	33.18	25.56	Clay Loam	10.77	1.79	0.188
	B	15.50"+	36.56	41.18	22.26	Clay	9.912	1.303	0.157
263	A	0 - 15.50"	50.60	25.16	24.24	Sandy Loam	2.091	2.209	0.185
	B	15.50"+	50.74	29.12	20.14	Clay	3.364	1.291	0.154
264	A	0 - 15.0"	88.70	4.98	6.32	Loamy Sand	ND	0.573	0.09
	B	15.0"+	90.70	5.94	3.36	Sandy Clay Loam	ND	0.741	0.112
265	A	0 - 11.50"	66.20	10.80	23.00	Sandy Loam	7.133	1.446	0.168
	B	11.50"+	59.56	14.62	25.82	Sandy Loam	8.416	0.992	0.142
266	A	0 - 11.50"	78.14	5.50	16.36	Silt Loam	0.72	0.978	0.144
	B	11.50"+	75.72	4.36	19.92	Silt Clay Loam	5.423	0.686	0.124
267	A	0 - 11.50"	70.08	11.30	18.62	Sandy Loam	5.851	1.302	0.17
	B	11.50"+	68.58	11.70	19.72	Sandy Clay Loam	5.851	0.772	0.132
268	A	0 - 7.50"	65.12	8.44	26.44	Silt Loam	5.209	0.956	0.135
	B	7.50"+	68.38	8.30	23.32	Silt Loam	3.499	0.807	0.13
269	A	0 - 6.00"	84.60	4.26	11.14	Sandy Loam	66.9	3.762	0.284
	B	6.00"+	76.64	9.28	14.08	Sandy Clay Loam	ND	0.737	0.122

Table 1. Observations from physical and chemical properties test of ETPPRP Phase II plots.

PLOT	PROFILE	HORIZON/DEPTH RANGE	SAND (%)	CLAY (%)	SILT (%)	TEXTURAL CLASS	NH4 (ppm)	C (%)	N (%)
270	A	0 - 6.50"	40.50	17.72	41.76	Silt Loam	ND	2.167	0.206
	B	6.50"+	38.92	33.54	27.50	Silt Loam	ND	0.997	0.158
271	A	0 - 8.25"	75.92	5.90	18.18	Sandy Loam	2.166	1.889	0.176
	B	8.25"+	67.02	7.86	25.12	Sandy Loam	ND	0.773	0.118
272	A	0 - 8.5"	80.78	8.98	10.24	Sandy Loam	ND	1.774	0.144
	B	8.5"+	75.52	17.08	7.40	Sandy Clay Loam	ND	1.029	0.14
273	A	0 - 12"	76.14	6.46	17.40	Sandy Loam	ND	0.89	0.119
	B	12"+	77.02	7.50	15.48	Sandy Clay Loam	ND	0.637	0.11
274	A	0 - 11.50"	84.14	4.76	11.10	Sandy Loam	0.443	1.189	0.141
	B	11.50"+	78.14	7.72	14.14	Sandy Clay Loam	ND	0.605	0.118
275	A	0 - 12.00"	81.16	6.22	12.62	Sandy Loam	ND	1.932	0.183
	B	12.00"+	65.70	20.98	13.32	Sandy Clay Loam	ND	0.81	0.134
276	A								
	B								
277	A	0 - 10.00"	90.34	3.94	5.72	Sand	ND	0.962	0.127
	B	10.00"+	90.30	4.98	4.72	Sand	ND	0.806	0.118
278	A	0 - 7.00"	86.90	5.90	7.20	Loamy Sand	ND	1.251	0.136
	B	7.00"+	64.50	29.40	6.10	Sandy Clay Loam	ND	1.099	0.156
279	A	0 - 6.50"	76.50	5.58	17.92	Loamy Sand	ND	1.72	0.153
	B	6.50"+	84.64	5.50	9.86	Sandy Clay Loam	ND	0.668	0.112
280	A	0 - 4.50"	76.56	16.08	7.36	Sandy Loam	2.905	1.737	0.202
	B	4.50"+	82.52	11.08	6.40	Clay	ND	0.785	0.126
281	A	0 - 10.50"	85.30	3.94	10.76	Sandy Loam	0.443	1.504	0.15
	B	10.50"+	85.48	5.94	8.58	Sandy Loam	ND	0.741	0.118
282	A	0 - 4.50"	86.22	6.28	7.50	Loamy Sand	ND	0.967	0.134
	B	4.50"+	59.86	30.36	9.78	Sandy Clay Loam	ND	1.038	0.148
283	A	0 - 8.00"	85.56	12.86	1.58	Loamy Sand	ND	1.608	0.165
	B	8.00"+	86.88	10.76	2.36	Sandy Clay Loam	ND	0.81	0.132

Table 1. Observations from physical and chemical properties test of ETPPRP Phase II plots.

PLOT	PROFILE	HORIZON/DEPTH RANGE	SAND (%)	CLAY (%)	SILT (%)	TEXTURAL CLASS	NH4 (ppm)	C (%)	N (%)
284	A	0 - 4.00"	47.92	39.62	12.40	Sandy Loam	ND	1.687	0.181
	B	4.00"+	47.02	43.34	9.64	Clay	ND	0.978	0.152
285	A	0 - 5.50"	47.28	42.62	10.10	Sandy Loam	0.197	1.914	0.183
	B	5.50"+	39.32	46.62	14.06	Clay	ND	0.956	0.156
286	A	0 - 7.00"	84.64	6.14	9.22	Sandy Loam	1.182	1.897	0.168
	B	7.00"+	78.64	7.18	14.18	Sandy Clay Loam	ND	1.17	0.131
287	A	0 - 11.75"	62.28	8.72	29.00	Sandy Loam	ND	2.941	0.215
	B	11.75"+	59.28	12.72	28.00	Loam	ND	0.915	0.14
288	A	0 - 11.25"	84.08	7.28	8.64	Sandy Loam	5.811	2.881	0.234
	B	11.25"+	57.00	29.32	13.68	Loam	3.24	0.905	0.138
289	A	0 - 12.50"	54.64	11.54	33.82	Sandy Loam	5.603	2.17	0.184
	B	12.50"+	52.72	18.50	28.78	Loam	3.324	0.78	0.13
290	A	0 - 10.50"	53.90	8.70	37.40	Sandy Loam	4.36	2.143	0.183
	B	10.50"+	39.10	34.70	26.20	Sandy Loam	3.117	0.97	0.153
291	A	0 - 15"	72.14	2.18	25.68	Sandy Loam	3.531	1.442	0.152
	B	15"+	57.90	16.26	25.84	Loam	29.1	0.761	0.127
292	A	0 - 11.50"	48.46	16.02	35.52	Sandy Loam	4.36	1.331	0.162
	B	11.50"+	47.88	20.00	32.12	Loam	3.946	0.885	0.138
293	A	0 - 3.50"	58.30	9.34	32.36	Sandy Loam	8.711	2.031	0.186
	B	3.50"+	51.84	16.02	32.14	Loam	3.531	0.996	0.132
294	A	0 - 7.25"	76.52	5.94	17.54	Sandy Loam	3.946	1.066	0.131
	B	7.25"+	67.70	7.86	24.44	Sandy Clay Loam	2.703	0.827	0.123
295	A	0 - 13.50"	89.42	5.58	5.00	Sand	6.846	0.867	0.12
	B	13.50"+	84.38	4.58	11.04	Loamy sand	3.117	0.685	0.108
296	A	0 - 9"	74.20	7.34	18.46	Sandy Loam	4.36	1.459	0.157
	B	9"+	75.58	12.66	11.76	Sandy Loam	2.703	0.698	0.126
297	A	0 - 7.5"	83.78	10.98	5.24	Sandy Loam	4.782	2.288	0.205
	B	7.5"+	60.66	37.00	2.34	Sandy Clay Loam	6.492	1.074	0.162

Table 1. Observations from physical and chemical properties test of ETPPRP Phase II plots.

PLOT	PROFILE	HORIZON/DEPTH RANGE	SAND (%)	CLAY (%)	SILT (%)	TEXTURAL CLASS	NH4 (ppm)	C (%)	N (%)
298	A	0 - 14.00"	77.20	7.72	15.08	Loamy Sand	2.91	0.811	0.126
	B	14.00"+	68.02	25.82	6.16	Sandy loam	3.324	0.805	0.151
299	A	0 - 5"	68.78	15.72	15.50	Sandy Loam	2.703	1.192	0.153
	B	5"+	41.66	42.72	15.62	Clay	4.153	1.171	0.183
300	A	0 - 8.5"	90.24	8.64	1.12	Sandy Loam	3.739	1.344	0.162
	B	8.5"+	84.50	5.58	9.92	Sandy Clay	2.703	0.629	0.116
301	A	0 - 8.5"	58.74	20.98	20.28	Sandy Loam	4.36	1.851	0.211
	B	8.5"+	59.12	28.58	12.30	Clay	3.117	1.191	0.178
302	A	0 - 13.00"	78.52	8.76	12.72	Loamy Sand	4.775	2.69	0.197
	B	13.00"+	61.20	14.90	23.90	Loamy Sand	3.324	2.387	0.235
303	A	0 - 5.00"	75.94	6.04	18.02	Loam	17	0.558	0.092
	B	5.00"+	73.70	8.08	18.22	Loam	2.703	0.724	0.113
304	A	0 - 9.00"	76.48	12.04	11.48	Sandy loam	4.36	1.552	0.145
	B	9.00"+	73.80	17.22	8.94	Sandy Clay Loam	7.468	0.88	0.127
305	A	0 - 7"	72.44	14.34	13.22	Sandy Loam	3.499	1.574	0.161
	B	7"+	68.25	25.08	6.67	Clay	4.354	0.89	0.154
306	A	0 - 5"	77.92	2.76	19.32	Sandy Loam	4.782	1.32	0.162
	B	5"+	68.66	9.86	21.48	Sandy Loam	3.072	0.695	0.135
307	A	0 - 10.50"	73.46	5.72	20.82	Sandy Loam	3.739	1.564	0.161
	B	10.50"+	66.20	5.94	27.86	Sandy Loam	1.874	0.803	0.126
308	A	0 - 11.25"	81.92	5.94	12.14	Sandy Loam	3.739	1.334	0.151
	B	11.25"+	80.74	5.94	13.32	Sandy Clay loam	2.081	0.67	0.119
309	A	0 - 9.50"	82.70	5.08	12.22	Sandy Loam	4.153	1.725	0.16
	B	9.50"+	76.30	8.30	15.40	Sandy Clay Loam	1.874	0.769	0.118
310	A	0 - 7.75"	76.56	8.00	15.44	Sandy Loam	2.91	1.739	0.165
	B	7.75"+	67.28	13.68	19.04	Sandy Loam	2.081	0.686	0.127
311	A	0 - 8.75"	85.66	4.98	9.36	Sandy Loam	3.117	2.524	0.218
	B	8.75"+	56.42	11.08	32.50	Sandy Loam	3.946	0.686	0.123

Table 1. Observations from physical and chemical properties test of ETPPRP Phase II plots.

PLOT	PROFILE	HORIZON/DEPTH RANGE	SAND (%)	CLAY (%)	SILT (%)	TEXTURAL CLASS	NH4 (ppm)	C (%)	N (%)
312	A	0 - 6.00"	84.60	8.18	7.22	Sandy Loam	8.504	2.073	0.192
	B	6.00"+	78.42	12.30	9.28	Clay	2.288	1.022	0.137
313	A	0 - 2.50"	86.70	11.86	1.44	Loamy Sand	3.531	1.782	0.162
	B	2.50"+	78.00	13.90	8.10	Loamy Sand	3.531	0.962	0.129
314	A	0 - 8.5"	61.28	5.50	33.22	Loam	4.996	3.924	0.298
	B	8.5"+	36.20	45.86	17.94	Clay	12.26	1.029	0.163
315	A	0 - 8.5"	56.20	9.94	33.86	Loam	3.927	2.503	0.238
	B	8.5"+	42.66	25.08	32.26	Clay	2.217	0.826	0.147
316	A	0 - 6.75"	75.30	12.98	11.72	Sandy loam	4.567	1.577	0.163
	B	6.75"+	46.34	44.94	8.72	Clay	2.496	1.37	0.181
317	A	0 - 10.50"	67.52	15.86	16.62	Sandy Loam	7.347	2.46	0.238
	B	10.50"+	62.04	14.30	23.66	Sandy Loam	3.927	0.922	0.157
318	A								
	B								
319	A	0 - 21.50"	91.28	3.62	5.10	Sand	6.225	1.622	0.138
	B	21.50"+	81.32	4.62	14.06	Sand	1.252	0.612	0.111
320	A	0 - 14.25"	70.92	7.54	21.58	Sandy Loam	4.982	2.016	0.193
	B	14.25"+	68.84	16.54	14.62	Sandy Loam	1.46	0.921	0.135
321	A	0 - 6.25"	87.50	3.58	8.92	Sandy Loam	4.775	3.941	0.249
	B	6.23"+	77.50	5.58	16.92	Sandy Loam	2.081	0.553	0.09
322	A	0 - 24.00"	91.20	4.34	4.46	Loamy Sand	2.003	0.845	0.138
	B	24.00"+	84.20	6.36	9.44	Loamy Sand	2.43	0.612	0.13
323	A	0 - 4.50"	58.82	10.94	30.24	Loamy Sand	4.153	1.519	0.169
	B	4.50"+	44.00	16.86	39.14	Sandy Loam	2.496	0.791	0.126
324	A								
	B								
325	A	0 - 15.50"	95.24	2.72	2.04	Loamy sand	1.252	0.924	0.139
	B	15.50"+	95.92	2.80	1.28	Loamy Sand	0.838	0.6	0.116

Table 1. Observations from physical and chemical properties test of ETPPRP Phase II plots.

PLOT	PROFILE	HORIZON/DEPTH RANGE	SAND (%)	CLAY (%)	SILT (%)	TEXTURAL CLASS	NH4 (ppm)	C (%)	N (%)
326	A								
	B								
327	A	0 - 11"	80.12	6.44	13.44	Sandy Loam	3.286	1.144	0.168
	B	11"+	71.70	5.94	22.36	Clay Loam	2.003	0.791	0.142
328	A	0 - 7"	68.70	11.82	19.48	Sandy Loam	7.988	2.526	0.239
	B	7"+	53.92	23.76	22.32	Clay	4.568	1.55	0.209
329	A	0 - 8.5"	72.18	6.72	21.10	Sandy Loam	4.568	1.856	0.206
	B	8.5"+	74.18	6.72	19.10	Clay loam	2.644	0.92	0.154
330	A	0 - 14.25"	80.56	5.04	14.40	Sandy Loam	3.927	1.435	0.159
	B	14.25"+	76.58	7.44	15.98	Loam	3.286	0.655	0.121
331	A	0 - 10.75"	74.42	4.88	20.70	Sandy Loam	2.703	1.155	0.127
	B	10.75"+	67.34	9.27	23.30	Loam	2.288	0.658	0.117
332	A	0-5"	77.66	18.34	4.00	Sandy Loam	6.432	1.781	0.183
	B	5"+	47.78	46.44	5.78	Clay	2.703	1.594	0.191

Table 2. Descriptive statistics of climate variables from ETPPRP Phase II plots range from Jan 1st, 2000 to Dec 31st, 2017.

Variable	Mean	Std. Dev	Minimum	Maximum
mApct	3.3072	0.1636	2.9095	3.6591
mAtmax	15.612	0.6659	14.210	16.978
mAtmin	4.6380	0.8483	3.0297	6.7791
mAtmean	10.130	0.7353	8.6200	11.567
mBpct	3.5776	0.0599	3.4321	3.6728
mBtmax	25.547	0.4860	24.321	26.330
mBtmin	14.032	0.7088	12.716	15.883
mBtmean	19.799	0.5485	18.518	20.725
mCpct	3.8449	0.5217	2.8796	5.0937
mCtmax	34.646	0.4504	33.108	35.106
mCtmin	23.177	0.3395	22.829	24.365
mCtmean	28.912	0.1174	28.612	29.095
mDpct	3.7700	0.2311	3.1838	4.1851
mDtmax	23.889	0.3263	23.229	24.613
mDtmin	12.141	0.7132	10.955	14.135
mDtmean	18.004	0.5102	16.081	19.019
mYpct	3.6653	0.2189	3.1449	4.1437
mYtmax	25.673	0.3199	24.926	26.276
mYtmin	14.179	0.6317	13.120	15.958
mYtmean	19.926	0.4166	19.089	20.727

Table 3. Soil texture class comparison of ETPPRP Phase II and online data.

PLOT	COUNTY	PROFILE	TEXTURE CLASS	ONLINE TEXTURE DATA
200	SABINE	A	Sandy Loam	Loamy Sand
		B	Sandy Clay Loam	Sandy Clay loam
201	NEWTON	A	Loamy Sand	Loamy Sand
		B	Sandy Clay loam	Sandy Clay loam
202	SABINE	A		
		B		
203	NEWTON	A	Sandy Loam	Fine Sandy Loam
		B	Sandy Loam	Clay
204	SABINE	A		
		B		
205	JASPER	A	Sandy Loam	Fine Sandy Loam
		B	Sandy Loam	Clay
206	JASPER	A	Loamy Sand	Loamy Sand
		B	Sandy Clay loam	Sandy Clay loam
207	JASPER	A	Loamy sand	Loamy Sand
		B	Sandy Clay loam	Sandy Clay loam
208	JASPER	A	Loamy Sand	Loamy Sand
		B	Sandy Clay loam	Sandy Clay loam
209	JASPER	A	Sandy Loam	Very fine sandy Loam
		B	Sandy Loam	Very fine sandy Loam
210	JASPER	A	Sandy Loam	Very fine sandy Loam
		B	Loam	Loam
211	JASPER	A	Sandy Loam	Very fine sandy Loam
		B	Loam	Loam
212	JASPER	A		
		B		
213	NEWTON	A	Silt Loam	Silt Loam
		B	Silt Loam	Silt Loam
214	JASPER	A		
		B		

Table 3. Soil texture class comparison of ETPPRP Phase II and online data.

PLOT	COUNTY	PROFILE	TEXTURE CLASS	ONLINE TEXTURE DATA
215	JASPER	A	Silt Loam	Silt Loam
		B	Silt Loam	Silt Loam
216	JASPER	A	Sandy Loam	Very fine sandy Loam
		B	Sandy Loam	Fine Sandy Loam
217	JASPER	A	Sandy Loam	Very fine sandy Loam
		B	Loam	Loam
218	JASPER	A	Sandy loam	Silt Loam
		B	Clay loam	Silt Loam
219	NACOGDOCHES	A	Sandy Loam	Very fine sandy Loam
		B	Clay	Clay
220	PANOLA	A	Clay Loam	Clay Loam
		B	Sandy Clay loam	Sandy Clay loam
221	PANOLA	A	Sandy Loam	Silt Loam
		B	Sandy Loam	Silt Loam
222	PANOLA	A	Silt Loam	Silt Loam
		B	Silty Clay	Silty Clay
223	PANOLA	A	Sandy Loam	Very fine sandy Loam
		B	Loam	Loam
224	DE SOTO	A	Sandy Loam	Fine Sandy Loam
		B	Sandy Clay loam	Sandy Clay loam
225	NACOGDOCHES	A		
		B		
226	NACOGDOCHES	A		
		B		
227	NACOGDOCHES	A	Sandy Clay Loam	Fine Sandy Loam
		B	Clay	Loam

Table 3. Soil texture class comparison of ETPPRP Phase II and online data.

PLOT	COUNTY	PROFILE	TEXTURE CLASS	ONLINE TEXTURE DATA
228	SHELBY	A	Loamy Sand	Loamy fine sand
		B	Sandy Loam	Loamy Fine Sand
229	SHELBY	A	Loamy Sand	Fine Sandy Loam
		B	Clay	Clay
230	SAN AUGUSTINE	A	Sandy Loam	Very fine sandy Loam
		B	Clay	Clay
231	SAN AUGUSTINE	A	Sandy Loam	Fine Sandy Loam
		B	Sandy Clay loam	Sandy Clay loam
232	NEWTON	A	Sandy Loam	Fine Sandy Loam
		B	Silty Clay	Silty Clay
233	NEWTON	A	Loamy Sand	Loamy fine sand
		B	Loamy Sand	Loamy fine sand
234	NEWTON	A	Loamy sand	Loamy fine sand
		B	Loamy sand	Loamy fine sand
235	DE SOTO	A	Sandy Loam	Very fine sandy Loam
		B	Clay	Clay
236	CHEROKEE	A	Loamy Sand	Loamy fine sand
		B	Loamy Sand	Loamy fine sand
237	CHEROKEE	A	Sandy Loam	Fine Sandy Loam
		B	Sandy Clay Loam	Sandy Clay Loam
238	CHEROKEE	A		
		B		
239	RUSK	A	Loamy sand	Loamy fine sand
		B	Loamy Sand	Loamy fine sand
240	PANOLA	A	Loamy Sand	Fine Sandy Loam
		B	Sandy Clay Loam	Clay
241	PANOLA	A	Sandy Loam	Very fine sandy Loam

Table 3. Soil texture class comparison of ETPPRP Phase II and online data.

PLOT	COUNTY	PROFILE	TEXTURE CLASS	ONLINE TEXTURE DATA
242	NACOGDOCHES	A	Sandy Loam	Fine Sandy Loam
		B	Clay	Clay
243	NACOGDOCHES	A		
		B		
244	NEWTON	A	Loam	Loam
		B	Sandy Clay Loam	Sandy Clay loam
245	NEWTON	A	Loamy Sand	Loamy Sand
		B	Sandy Clay loam	Sandy Clay loam
246	NEWTON	A		
		B		
247	SABINE	A	Sandy Loam	Fine Sandy Loam
		B	Clay	Clay
248	SABINE	A	Sand	Loamy Sand
		B	Sand	Sandy Clay loam
249	VERNON	A	Loamy Sand	Loamy fine sand
		B	Sandy Clay loam	Sandy Clay loam
250	VERNON	A	Silt Loam	Silt Loam
		B	Clay	Clay
251	VERNON	A	Silt Loam	Silt Loam
		B	Clay	Clay
252	VERNON	A	Sandy Loam	Fine Sandy Loam
		B	Loam	Loam
253	DE SOTO	A	Sandy Loam	Fine Sandy Loam
		B	Clay Loam	Clay Loam
254	DE SOTO	A		
		B		
255	SABINE	A	Sandy Loam	Fine Sandy Loam
		B	Clay	Clay

Table 3. Soil texture class comparison of ETPPRP Phase II and online data.

PLOT	COUNTY	PROFILE	TEXTURE CLASS	ONLINE TEXTURE DATA
256	SABINE	A	Sandy Loam	Fine Sandy Loam
		B	Sandy Clay Loam	Clay
257	SABINE	A		
		B		
258	SABINE	A	Loamy Sand	Fine Sandy Loam
		B	Sandy loam	Clay
259	PANOLA	A		
		B		
260	SHELBY	A	Sandy Loam	Fine Sandy Loam
		B	Clay	Clay
261	SAN AUGUSTINE	A	Loamy Sand	Loamy Fine Sand
		B	Sand Clay Loam	Sand Clay Loam
262	NACOGDOCHES	A	Clay Loam	Clay Loam
		B	Clay	Clay
263	SABINE	A	Sandy Loam	Fine Sandy Loam
		B	Clay	Clay
264	NEWTON	A	Loamy Sand	Loamy Sand
		B	Sandy Clay Loam	Sandy Clay Loam
265	RED RIVER	A	Sandy Loam	Silt Loam
		B	Sandy Loam	Clay
266	RED RIVER	A	Silt Loam	Silt Loam
		B	Silt Clay Loam	Silt Clay Loam
267	NATCHITOCHES	A	Sandy Loam	Fine Sandy Loam
		B	Sandy Clay Loam	Sandy Clay Loam
268	NATCHITOCHES	A	Silt Loam	Silt Loam
		B	Silt Loam	Silt Loam

Table 3. Soil texture class comparison of ETPPRP Phase II and online data.

PLOT	COUNTY	PROFILE	TEXTURE CLASS	ONLINE TEXTURE DATA
269	TYLER	A	Sandy Loam	Fine Sandy Loam
		B	Sandy Clay Loam	Sandy Clay Loam
270	TYLER	A	Silt Loam	Silt Loam
		B	Silt Loam	Silt Loam
271	TYLER	A	Sandy Loam	Very Fine Sandy Loam
		B	Sandy Loam	Very Fine Sandy Loam
272	POLK	A	Sandy Loam	Fine Sandy Loam
		B	Sandy Clay Loam	Sandy Clay Loam
273	TYLER	A	Sandy Loam	Fine Sandy Loam
		B	Sandy Clay Loam	Sandy Clay Loam
274	TYLER	A	Sandy Loam	Fine Sandy Loam
		B	Sandy Clay Loam	Sandy Clay Loam
275	TYLER	A	Sandy Loam	Fine Sandy Loam
		B	Sandy Clay Loam	Sandy Clay Loam
276	HARDIN	A		
		B		
277	JASPER	A	Sand	Loamy Sand
		B	Sand	Sandy Clay Loam
278	JASPER	A	Loamy Sand	Loamy Sand
		B	Sandy Clay Loam	Sandy Clay Loam
279	JASPER	A	Loamy Sand	Loamy Sand
		B	Sandy Clay Loam	Sandy Clay Loam
280	JASPER	A	Sandy Loam	Fine Sandy Loam
		B	Clay	Clay
281	TYLER	A	Sandy Loam	Very Fine Sandy Loam
		B	Sandy Loam	Very Fine Sandy Loam

Table 3. Soil texture class comparison of ETPPRP Phase II and online data.

PLOT	COUNTY	PROFILE	TEXTURE CLASS	ONLINE TEXTURE DATA
282	JASPER	A	Loamy Sand	Loamy Fine Sand
		B	Sandy Clay Loam	Sandy Clay Loam
283	JASPER	A	Loamy Sand	Loamy Fine Sand
		B	Sandy Clay Loam	Sandy Clay Loam
284	NEWTON	A	Sandy Loam	Fine Sandy Loam
		B	Clay	Clay
285	NEWTON	A	Sandy Loam	Fine Sandy Loam
		B	Clay	Clay
286	NEWTON	A	Sandy Loam	Fine Sandy Loam
		B	Sandy Clay Loam	Sandy Clay Loam
287	JASPER	A	Sandy Loam	Very Fine Sandy Loam
		B	Loam	Loam
288	JASPER	A	Sandy Loam	Fine Sandy Loam
		B	Loam	Loam
289	JASPER	A	Sandy Loam	Fine Sandy Loam
		B	Loam	Loam
290	JASPER	A	Sandy Loam	Fine Sandy Loam
		B	Sandy Loam	Sandy Loam
291	JASPER	A	Sandy Loam	Fine Sandy Loam
		B	Loam	Loam
292	JASPER	A	Sandy Loam	Sandy Loam
		B	Loam	Loam
293	JASPER	A	Sandy Loam	Fine Sandy Loam
		B	Loam	Loam
294	NEWTON	A	Sandy Loam	Fine Sandy Loam
		B	Sandy Clay Loam	Sandy Clay Loam
295	NEWTON	A	Sand	Fine Sandy Loam
		B	Loamy sand	Loam

Table 3. Soil texture class comparison of ETPPRP Phase II and online data.

PLOT	COUNTY	PROFILE	TEXTURE CLASS	ONLINE TEXTURE DATA
296	HARDIN	A	Sandy Loam	Very Fine Sandy Loam
		B	Sandy Loam	Very Fine Sandy Loam
297	NEWTON	A	Sandy Loam	Fine Sand Loam
		B	Sandy Clay Loam	Sandy Clay Loam
298	NEWTON	A	Loamy Sand	Loamy Fine Sand
		B	Sandy loam	Loamy Fine Sand
299	ANGELINA	A	Sandy Loam	Fine Sandy Loam
		B	Clay	Clay
300	ANGELINA	A	Sandy Loam	Fine Sandy Loam
		B	Sandy Clay	Clay
301	ANGELINA	A	Sandy Loam	Fine Sandy Loam
		B	Clay	Clay
302	NEWTON	A	Loamy Sand	Loamy Fine Sand
		B	Loamy Sand	Loamy Fine Sand
303	JASPER	A	Loam	Loam
		B	Loam	Loam
304	JASPER	A	Sandy loam	Fine Sandy Loam
		B	Sandy Clay Loam	Sandy Clay Loam
305	SABINE	A	Sandy Loam	Fine Sandy Loam
		B	Clay	Clay
306	SAN AUGUSTINE	A	Sandy Loam	Fine Sandy Loam
		B	Sandy Loam	Fine Sandy Loam
307	ANGELINA	A	Sandy Loam	Fine Sandy Loam
		B	Sandy Loam	Fine Sandy Loam
308	ANGELINA	A	Sandy Loam	Fine Sandy Loam
		B	Sandy Clay loam	Sandy Clay Loam
309	TYLER	A	Sandy Loam	Fine Sandy Loam
		B	Sandy Clay Loam	Sandy Clay Loam

Table 3. Soil texture class comparison of ETPPRP Phase II and online data.

PLOT	COUNTY	PROFILE	TEXTURE CLASS	ONLINE TEXTURE DATA
310	TYLER	A	Sandy Loam	Fine Sandy Loam
		B	Sandy Loam	Fine Sandy Loam
311	TYLER	A	Sandy Loam	Very Fine Sandy Loam
		B	Sandy Loam	Very Fine Sandy Loam
312	TYLER	A	Sandy Loam	Very Fine Sandy Loam
		B	Clay	Clay
313	NEWTON	A	Loamy Sand	Loamy Fine Sand
		B	Loamy Sand	Loamy Fine Sand
314	NACOGDOCHES	A	Loam	Loam
		B	Clay	Clay
315	ANGELINA	A	Loam	Loam
		B	Clay	Clay
316	ANGELINA	A	Sandy loam	Fine Sandy Loam
		B	Clay	Clay
317	ANGELINA	A	Sandy Loam	Very Fine Sandy Loam
		B	Sandy Loam	Clay
318	SAN AUGUSTINE	A		
		B		
319	HARDIN	A	Sand	Fine Sand
		B	Sand	Fine Sand
320	HARDIN	A	Sandy Loam	Very Fine Sandy Loam
		B	Sandy Loam	Very Fine Sandy Loam
321	HARDIN	A	Sandy Loam	Very Fine Sandy Loam
		B	Sandy Loam	Very Fine Sandy Loam
322	CHEROKEE	A	Loamy Sand	Loamy Fine Sand
		B	Loamy Sand	Loamy Fine Sand

Table 3. Soil texture class comparison of ETPPRP Phase II and online data.

PLOT	COUNTY	PROFILE	TEXTURE CLASS	ONLINE TEXTURE DATA
323	JASPER	A	Loamy Sand	Loamy Fine Sand
		B	Sandy Loam	Very Fine Sandy Loam
324	JASPER	A		
		B		
325	ORANGE	A	Loamy sand	Loamy Fine Sand
		B	Loamy Sand	Loamy Fine Sand
326	NACOGDOCHES	A		
		B		
327	POLK	A	Sandy Loam	Very Fine Sandy Loam
		B	Clay Loam	Clay Loam
328	POLK	A	Sandy Loam	Very Fine Sandy Loam
		B	Clay	Clay
329	POLK	A	Sandy Loam	Very Fine Sandy Loam
		B	Clay loam	Clay loam
330	ANGELINA	A	Sandy Loam	Fine Sandy Loam
		B	Loam	Loam
331	ANGELINA	A	Sandy Loam	Fine Sandy Loam
		B	Loam	Loam
332	ANGELINA	A	Sandy Loam	Fine Sandy Loam
		B	Clay	Clay

Table 4. Pearson's correlation matrix among soil variables and coefficient parameters

	β_1	β_2	ASD	BSD	ACY	BCY	AST	BST	ANH	BNH	ACG	BCG	ANG	BNG
β_1	1.00	0.85	-0.01	-0.02	0.00	0.01	0.01	0.02	-0.03	-0.03	0.11	0.06	0.06	0.05
β_2	0.85	1.00	-0.01	-0.02	-0.02	0.01	0.03	0.01	-0.05	-0.06	0.03	0.08	0.05	0.11
ASD	-0.01	-0.01	1.00	0.82	-0.70	-0.56	-0.81	-0.57	0.03	-0.23	-0.30	-0.28	-0.38	-0.40
BSD	-0.02	-0.02	0.82	1.00	-0.60	-0.78	-0.64	-0.57	0.03	-0.24	-0.37	-0.41	-0.43	-0.55
ACY	0.00	-0.02	-0.70	-0.60	1.00	0.71	0.14	0.03	-0.06	0.16	0.19	0.44	0.30	0.50
BCY	0.01	0.01	-0.56	-0.78	0.71	1.00	0.19	-0.07	-0.08	0.27	0.29	0.51	0.34	0.66
AST	0.01	0.03	-0.81	-0.64	0.14	0.19	1.00	0.76	0.01	0.19	0.25	0.03	0.28	0.14
BST	0.02	0.01	-0.57	-0.57	0.03	-0.07	0.76	1.00	0.07	0.02	0.22	-0.01	0.24	0.01
ANH	-0.03	-0.05	0.03	0.03	-0.06	-0.08	0.01	0.07	1.00	-0.03	-0.09	-0.03	-0.10	-0.07
BNH	-0.03	-0.06	-0.23	-0.24	0.16	0.27	0.19	0.02	-0.03	1.00	0.16	0.17	0.18	0.18
ACG	0.11	0.03	-0.30	-0.37	0.19	0.29	0.25	0.22	-0.09	0.16	1.00	0.39	0.90	0.39
BCG	0.06	0.08	-0.28	-0.41	0.44	0.51	0.03	-0.01	-0.03	0.17	0.39	1.00	0.42	0.87
ANG	0.06	0.05	-0.38	-0.43	0.30	0.34	0.28	0.24	-0.10	0.18	0.90	0.42	1.00	0.51
BNG	0.05	0.11	-0.40	-0.55	0.50	0.66	0.14	0.01	-0.07	0.18	0.39	0.87	0.51	1.00

Table 5. Pearson's correlation matrix among climate factors and coefficient parameters.

	β_1	β_2	mApct	mAtmax	mAtmin	mAtmean	mBpct	mBtmax	mBtmin	mBtmean	mCpct	mCtmax	mCtmin
β_1	1.00	0.85	0.03	0.07	0.00	0.08	0.04	0.11	-0.01	-0.06	-0.02	0.10	-0.03
β_2	0.85	1.00	0.04	0.00	-0.10	-0.06	0.06	0.06	-0.11	-0.04	-0.14	0.22	-0.10
mApct	0.03	0.04	1.00	-0.14	0.04	-0.06	0.93	-0.25	0.04	-0.12	0.19	-0.39	-0.05
mAtmax	0.07	0.00	-0.14	1.00	0.91	0.97	-0.38	0.92	0.89	0.96	0.88	-0.50	0.64
mAtmin	0.00	-0.10	0.04	0.91	1.00	0.98	-0.15	0.70	1.00	0.93	0.97	-0.78	0.88
mAtmean	0.08	-0.07	-0.06	0.97	0.98	1.00	-0.27	0.81	0.97	0.98	0.95	-0.67	0.79
mBpct	0.04	0.06	0.93	-0.38	-0.15	-0.27	1.00	-0.50	-0.14	-0.34	0.01	-0.32	-0.11
mBtmax	0.11	0.06	-0.25	0.92	0.70	0.81	-0.50	1.00	0.68	0.86	0.67	-0.15	0.34
mBtmin	-0.01	-0.11	0.04	0.89	1.00	0.97	-0.14	0.68	1.00	0.92	0.96	-0.79	0.89
mBtmean	-0.06	-0.04	-0.12	0.96	0.93	0.98	-0.34	0.86	0.92	1.00	0.89	-0.56	0.72
mCpct	-0.02	-0.14	0.19	0.88	0.97	0.95	0.01	0.67	0.96	0.89	1.00	-0.82	0.81
mCtmax	0.10	0.22	-0.39	-0.50	-0.78	-0.67	-0.32	-0.15	-0.79	-0.56	-0.82	1.00	-0.86
mCtmin	-0.03	-0.10	-0.05	0.64	0.88	0.79	-0.11	0.34	0.89	0.72	0.81	-0.86	1.00

Table 5. Pearson's correlation matrix among climate factors and coefficient parameters.

	β_1	β_2	mCtmean	mDpct	mDtmax	mDtmin	mDtmean	mYpct	mYtmax	mYtmin	mYtmean
β_1	1.00	0.85	0.16	-0.09	0.13	0.01	0.02	-0.09	0.15	0.00	0.09
β_2	0.85	1.00	0.28	0.04	0.09	-0.08	-0.03	-0.22	0.13	-0.10	-0.02
mCtmean	0.16	0.28	1.00	-0.60	0.23	-0.19	-0.09	-0.61	0.38	-0.22	-0.02
mDpct	-0.09	-0.22	-0.60	1.00	0.52	0.79	0.77	0.99	0.37	0.81	0.76
mDtmax	0.13	0.09	0.23	0.52	1.00	0.69	0.81	0.50	0.96	0.67	0.88
mDtmin	0.01	-0.08	-0.19	0.79	0.69	1.00	0.94	0.83	0.49	1.00	0.95
mDtmean	0.02	-0.03	-0.09	0.77	0.81	0.94	1.00	0.78	0.67	0.94	0.97
mYpct	-0.09	-0.22	-0.61	0.99	0.50	0.83	0.78	1.00	0.33	0.84	0.77
mYtmax	0.15	0.13	0.38	0.37	0.96	0.49	0.67	0.33	1.00	0.48	0.75
mYtmin	0.00	-0.10	-0.22	0.81	0.67	1.00	0.94	0.84	0.48	1.00	0.94
mYtmean	0.05	-0.02	-0.02	0.76	0.88	0.95	0.97	0.77	0.75	0.94	1.00

VITA

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