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Longer greenup periods associated with greater wood volume growth in managed pine stands

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ABSTRACT

Increasing forest productivity is important to meet future demand for forest products, and to improve resilience in the face of climate change. Forest productivity depends on many things, but the timing of leaf development (hereafter: "plant phenology") is especially important. However, our understanding of how plant phenology affects the productivity of managed forests, and how silviculture may in turn affect phenology, has been limited because of the spatial scale mismatch between phenological data and field experimental observations. In this study, we take advantage of a new 30 m satellite land surface phenology dataset and stand growth measurements from long-term experimental pine plantation sites in the southeastern United States to investigate the question: is stand growth related to remotely sensed phenology metrics? Multiple linear regression and random forest models were fitted to quantify the effect of phenology and silvicultural treatments on stand growth. We found that 1) Greater wood volume growth was associated with longer green up periods; 2) Fertilization elevated EVI2 measurement values during the whole growing season, especially in the winter; 3) Competing vegetation could affect remotely sensed observations and complicates interpretation of remotely sensed phenology metrics.

1. Introduction

Forests play an important role in our environment and economy. The demand for forest products is rising due to the continued increase of Earth's population, while land degradation and urbanization have significantly reduced productive forestland (Wear and Greis, 2002). Forest managers have applied increasingly intensive silvicultural practices including site preparation, competition control, fertilization, and genetic improvement to increase forest productivity (Fox et al., 2007). Although the impacts of climate change on forest productivity vary across the landscape (Boisvenue and Running, 2006), silvicultural practices may need to adapt in order to maintain forest productivity in a changing climate (Brang et al., 2014). Thus, understanding the interactive roles of climate change and silvicultural practices on forest productivity is important to maintain future ecosystem function and productivity in order to meet demand for wood products in the face of future climate change.

The definition of forest productivity varies (Grier, 1989). In an ecologist's perspective, intending to measure carbon storage, forest productivity could mean the total amount of plant material produced per unit area per year, net primary productivity (NPP). It could also mean net ecosystem production (NEP), which is NPP minus heterotrophic respiration (Kirschbaum et al., 2001). If we consider the environmental effects from forest animals, forest productivity could refer to aboveground net primary productivity (ANPP) as well. From a forest manager's view, however, forest productivity represents wood production per unit forest area per year. To better utilize data from the field experiments, here we use stand volume increment per unit area per year as the metric to represent forest productivity.

Although forest productivity depends on many factors, the timing of leaf development (hereafter: "plant phenology") is especially important. Plant phenology is one of the more sensitive indicators of environmental change (Parry et al., 2007). It responds not only to climate factors (Clark et al., 2014; Meng et al., 2020) such as temperature, light, and precipitation, but also to factors including soil moisture and nitrogen availability (Luo et al., 2020; Penuelas et al., 2009; Piao et al., 2019), performing as an integrative indicator of the living environment of vegetation. More importantly, phenological dynamics are critical to diagnose forest health problems and identify invasive species (Morisette et al., 2009), both of which directly affect forest productivity.

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In addition, changes in phenology strongly affect carbon cycling and energy balance in terrestrial ecosystems (Jeong et al., 2009; Piao et al., 2019). Plant phenology influences gross primary production (GPP) and net primary production (NPP) of forest ecosystems (Chang et al., 2019; Kaduk and Heimann, 1996; Keenan et al., 2014; Wang et al., 2017). The effect of altered phenological regimes on forest productivity appears to vary, with some studies indicating increased carbon uptake with warming-induced longer growing seasons (Keenan et al., 2014; Piao et al., 2017), and others indicating greater losses due to autumnal warming (Piao et al., 2008). As a direct measurement, stand volume growth represents a large portion of carbon sequestered from the atmosphere in forest systems (Albaugh et al., 1998; Gonzalez-Benecke et al., 2014) and is related to annual NPP, so it can also be an important indicator of the changing carbon dynamics. Plus, NPP across landscapes is difficult to measure accurately. Thus, understanding the relationship between phenology and stand volume growth can help us reduce uncertainty in carbon cycle estimates.

However, because of the spatial scale mismatch between phenological data (data typically collected at the leaf scale) and productivity measurements (at the stand or landscape scale), our knowledge of how phenology affects productivity, and how silviculture alters phenology is limited. Phenological observations from orbital platforms, land surface phenology (LSP), provide consistent phenological data over large areas and over long time periods (de Beurs and Henebry, 2004). But, until recently, available (i.e. operationally produced and accessible) LSP data have only been produced at coarse spatial resolution from sensors like the Advanced Very High-Resolution Radiometer (AVHRR; 8 km) and the Moderate Resolution Imaging Spectroradiometer (MODIS; 500 m). The spatial scales of these data are much coarser than typical silvicultural experimental plots (Albaugh et al., 2018), consequently, there have been few successful efforts to use LSP data to understand how productivity, silvicultural treatments, and phenology interact.

Recently, a 30 m spatial resolution LSP dataset was produced from Harmonized Landsat and Sentinel-2 imagery (HLS-LSP; Bolton et al., 2020). These HLS-LSP data, along with extensive field measurements from experimental forest stands throughout the southeastern United States, provide a unique opportunity to investigate the relationship between forest productivity, silvicultural treatments, and phenology.

In this study, we combined LSP data from satellite images with field measurements in a variety of models, to quantify the effect of phenology on productivity in managed stands, while controlling for a variety of silvicultural treatments. We mainly focused on exploring the question: is stand growth related to remotely sensed phenology metrics? Besides, we also investigated the potential of remotely sensed phenological observations in estimating forest productivity. Results like these are relevant for forest managers and ecological modelers, particularly in light of the influence that future climate variability may have on phenological processes..

2. Materials and methods

2.1. Data

2.1.1. Field measurements

Field measurements from long-term forest plantation field experiments (Albaugh et al., 2017; Vickers et al., 2012) distributed across the southeastern US were used in this study. Overall, there were 492 plots across 9 locations (Fig. 1a). Two experimental designs were used, one with fertilization and thinning as the main silvicultural treatments (RW19), and the other with fertilization, planting density, and genotype treatments (RW20). All sites were planted with loblolly pine (*Pinus taeda* L.). At RW19 sites, the same genotype, either control-pollinated (CP) or open-pollinated (OP), was planted in all plots at a given site whereas the RW20 sites had varietal, CP and OP genotypes planted in different plots at each site. RW19 research plots were installed in mid-rotation plantations between 12 and 16 years of age while RW20 research plots were

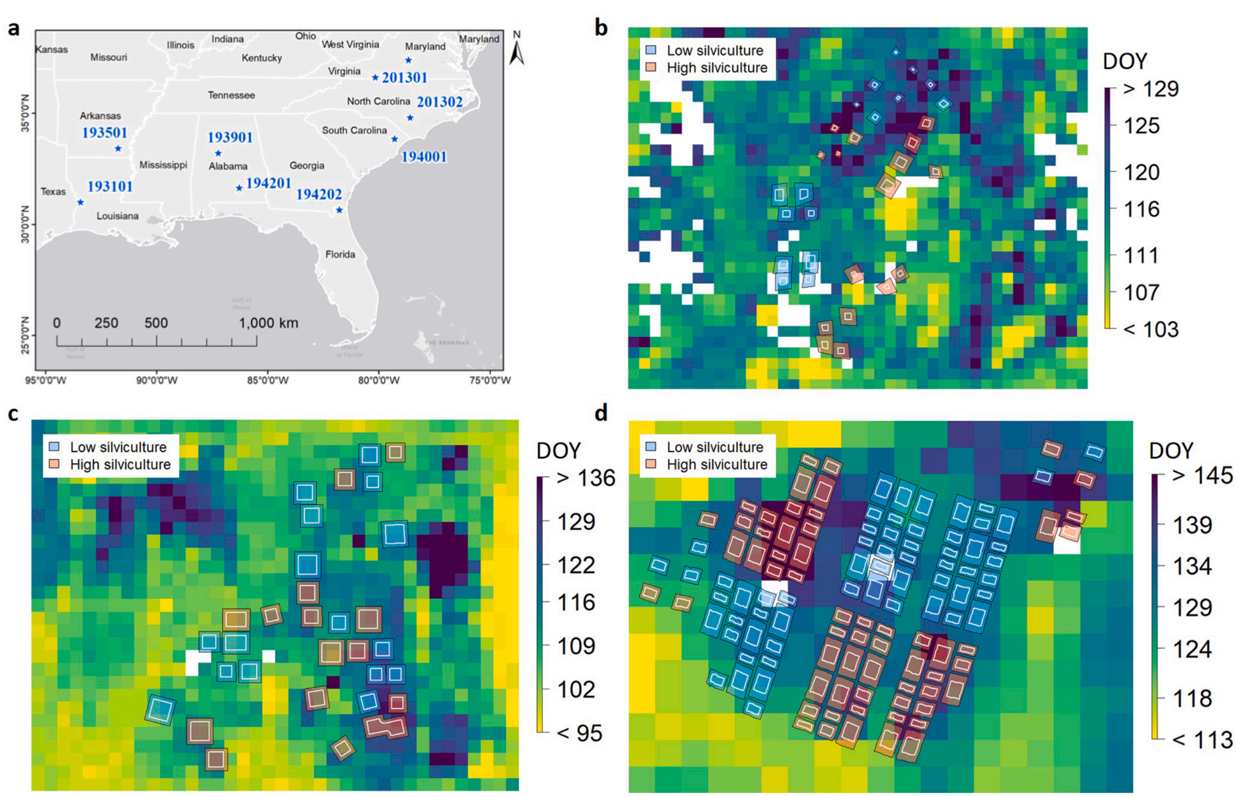

Fig. 1. a) Distribution of field sites in the southeastern US; b), c), and d) Examples of treatment plot design for RW193901, RW194201, and RW201302, respectively. Background images are MidGreenup layers in the 30 m LSP dataset derived from Harmonized Landsat 8 and Sentinel-2 (HLS) imagery. The unit of the background images is day of year (DOY).

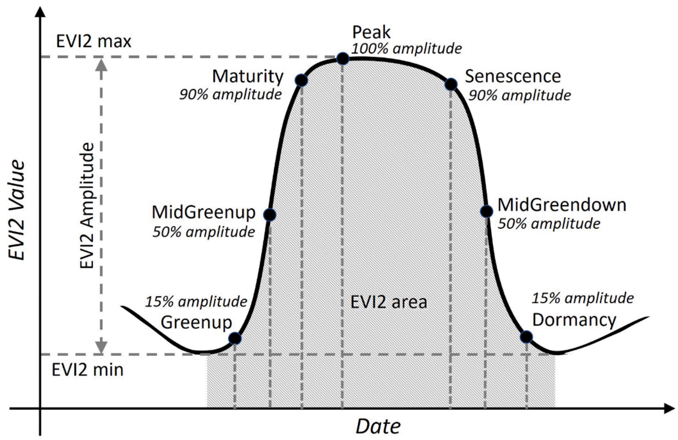

Fig. 2. Illustration of EVI2 time series and phenometrics. Greenup, MidGreenup, Maturity, Peak, Senescence, MidGreendown, and Dormancy are phenological dates in day-of-year (DOY) format; EVI2min, EVI2max, EVI2 amplitude, and EVI2 area are numerical metrics.

installed at site establishment. Four thinning treatments were applied at RW19 sites: thin to 247, 494, 741 and 1235 residual stems ha^{-1}; fertilizer treatments were: none or 224 and 28 kg ha^{-1} of elemental nitrogen and phosphorus, respectively, at study initiation plus 168 and 28 kg ha^{-1} of elemental nitrogen and phosphorus, respectively, eight years after installation. After thinning in all RW19 plots, competing vegetation (all vegetation that was not a planted pine) was sprayed with herbicide in order to suppress or kill the competing vegetation. Six genotypes (four clonal varieties, one CP and one OP) were planted at three initial densities (618, 1235, and 1853 stems ha^{-1}) at the RW20 sites. Silvicultural intensity at RW20 sites was operational (designed to follow current operational practices with competition control at planting and no fertilization to date) and intensive (designed to achieve near-maximum volume growth with competition control at planting and in years 1, 2, 5 and 10 along with fertilization at years 1, 5 and 10).

Individual tree height and diameter were measured annually at RW20 sites and annually for years 1-6 after initiation and every two years after that at the RW19 sites. Volume was estimated for each tree (Tasissa et al., 1997), summed for the plot and scaled to an area basis. Volume increment was calculated by subtracting the standing volume from the previous year from current year standing volume. Volume growth is dependent on stand density, though, it is easy to measure and directly reflects biomass growth in a unit area.

Fertilization and thinning were the silvicultural treatments examined in this study. Since fertilization timing and intensity were different at RW19 and RW20 sites, we categorized them into high and low silviculture levels based on different criteria. For RW19 sites, we categorized plots that were fertilized at study initiation (by 224 and 28 kg ha^{-1} of elemental nitrogen and phosphorus, respectively) and eight years after installation (by 168 and 28 kg ha^{-1} of elemental nitrogen and phosphorus, respectively) as high silvicultural plots; plots that did not receive any fertilizer as low silvicultural plots (e.g. Fig. 1b, and c). For RW20 sites, we categorized plots that had intensive silviculture as high silvicultural plots and plots that had operational silviculture as low silvicultural plots. Thinning was reflected by density levels, including 247, 494, 618, 741, 1235, and 1853 stems ha^{-1} (e.g. Fig. 1d).

2.1.2. *EVI2 time series and land surface phenology*

Land surface phenology observations were retrieved from HLS (Harmonized Landsat 8 and Sentinel-2) (Claverie el al., 2018) v1.4 time series using a modified version of the algorithm that produced the 30 m spatial resolution HLS-LSP product (Bolton et al., 2020). The HLS-LSP algorithm uses the smoothed time series of the two-band enhanced vegetation index (EVI2) (Jiang et al., 2008) to detect the timing of vegetation phenological transitions (phenometrics). Phenometrics are defined as the date when the smoothed EVI2 trajectories reach specific percentages of the EVI2 amplitude during the growing season (Fig. 2). Additionally, derivative quantities such as the integrated area under the EVI2 curve (EVI2 area), EVI2 maximum value, and the growing season EVI2 amplitude are also provided. We also computed the minimum growing season EVI2 value by subtracting the EVI2 maximum from the EVI2 amplitude. The EVI2 Peak metric layer, which records the timing of when EVI2 reaches its maximum by day of year, was not available in the HLS-LSP product when we conducted this analysis.

The HLS-LSP algorithm retrieves phenometrics only for vegetation cycles that exhibit some minimum amount of EVI2 variation during the growing season (EVI2 amplitude). This value was set at 0.1 to filter out non-vegetated pixels for the operationally produced product, which works well for most regions. However, many pixels in the experimental plots in our study had EVI2 amplitudes less than 0.1. Thus, we produced HLS-LSP data that covered our study regions using a lower EVI2 amplitude threshold: 0.03. Otherwise, our approach to retrieving

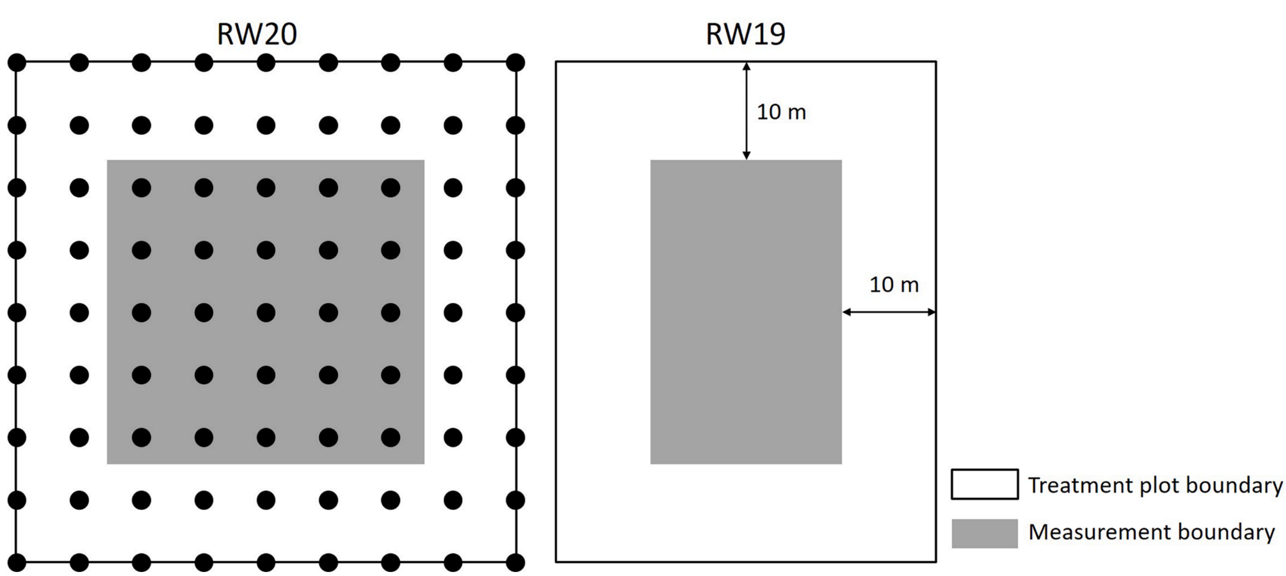

Fig. 3. Measurement boundary design in RW20 and RW19 sites. Black dots in RW20 represent individual trees.

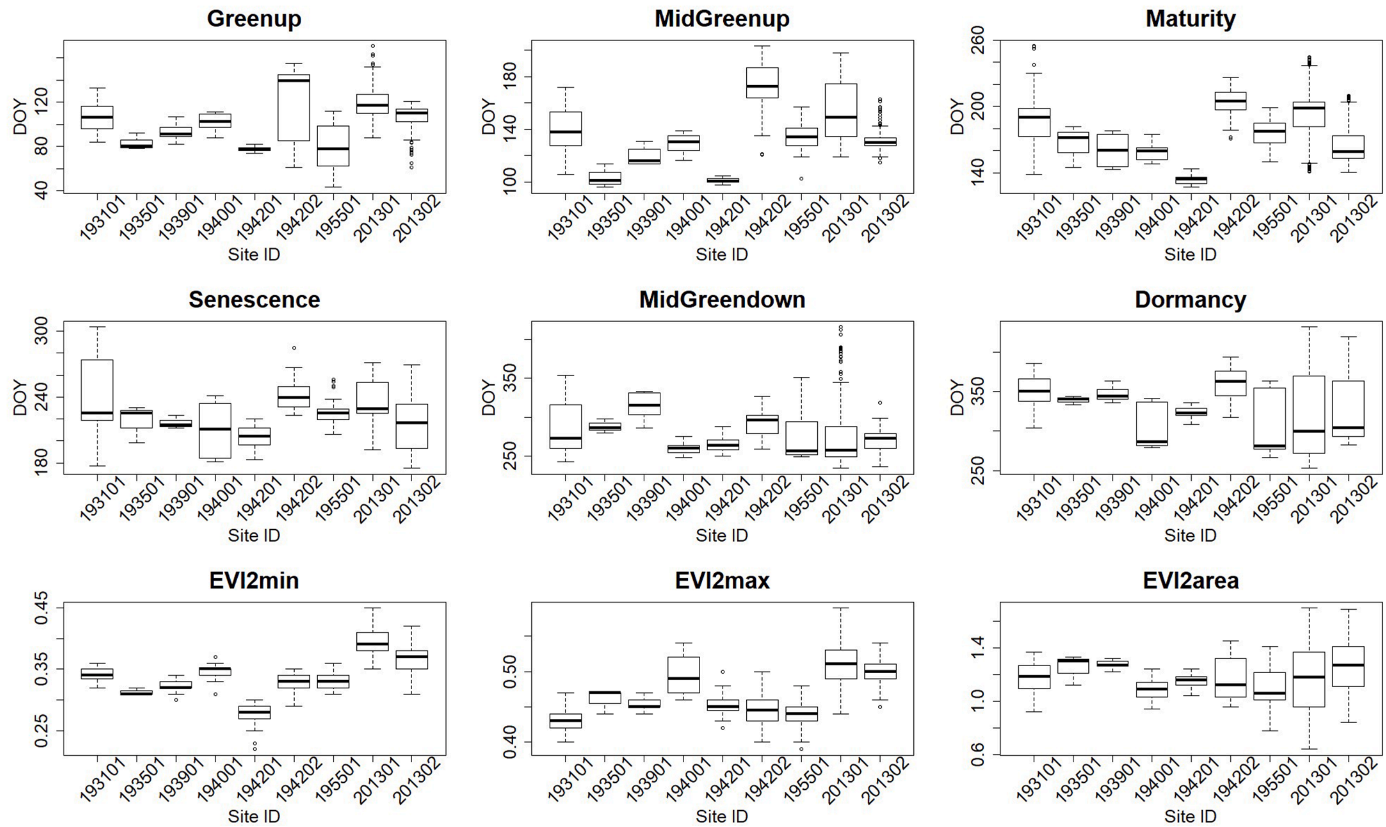

Fig. 4. Phenometrics retrieved from HLS-LSP dataset at RW19 and RW20 sites distributed across the southeastern United States. The unit of phenometrics is day of year (DOY).

phenometrics was identical to that described in Bolton et al. (2020).

To extract EVI2 time series and phenometrics for individual plots, mainly two strategies were used: 1) Measurement plot boundaries were used to avoid the influence of neighbor plots (Fig. 3). At RW20 sites, the treatment plot was a rectangle of 9 × 9 trees, and the measurement plot was the inner boundary around 5 × 5 trees. At RW19 sites, plot layouts are not as uniform as RW20 sites, the measurement plot boundaries were at least 10 m inside the treatment plot boundaries. 2) Since the dimensions of measurement boundaries vary across plots and sites (in our study, 51.7% of total plots were averaged by at least 3 pixels, 33.6% were averaged by 2 pixels, and the rest 14.7% were represented by only 1 pixel), if multiple pixels were covered by a boundary, pixel values were averaged; otherwise, the pixel that contains the measurement was extracted. The plots' design and their relative sizes to 30 m HLS-LSP pixels can be viewed in Fig. 1b, c, and d. The variability of phenometrics retrieved from HLS-LSP dataset are shown in Fig. 4.

Visual inspection was conducted to investigate the effects of silvicultural treatments on the trajectories of EVI2 time series. The EVI2 time series were averaged within categories defined by silvicultural intensity and stand density respectively for identifying site-independent patterns and reducing noise. Repeated measures ANOVA (Analysis of Variance) was also conducted across silviculture and density levels respectively to test the significance of effects on the mean values of phenometrics.

2.3. Volume growth model

Since HLS-LSP images are currently only available for 2016-2018, stand volume measurements from field experiments in the same time period were selected to perform further statistical analysis.

A multiple linear regression model was used to analyze the relationship between phenometrics, silvicultural treatments, and stand productivity (represented by volume growth). The outcome variable was volume increment per unit area, other variables were used as predictors. HLS-LSP predictors were: Greenup, MidGreenup, Maturity, Senescence, Greendown, Dormancy, EVI2min, EVI2max, and EVI2area. Silvicultural treatment (including low and high silviculture levels) and stand density (247, 494, 618, 741, 1235, and 1853 stems ha^{-1}) were categorical variables rather than numerical variables, and site ID was used to quantify random site effects, so we transformed them as factors in the model so that their values could be treated categorically. For the low silvicultural plots at RW20 sites, because competing vegetation was suppressed only at the time of planting, other vegetation was likely competing with crop trees for nutrients, light, water, and space. Including the RW20 low silvicultural plots in the productivity model would bias the model. Thus, in the multiple linear regression model, we removed records from the low silvicultural plots at RW20 sites. All the variable values were normalized so that they would all have means of zero and standard deviations of one.

Although the multiple linear regression model can provide a direct quantification of the individual effects of the variables, it assumes the relationship to be linear. Random forest model can quantify non-linear relationships and is good at making predictions, thus it was used here to evaluate the potential of phenology in estimating annual volume growth. Random forest (Breiman, 2001) is an algorithm that is built upon the decision tree learning model but takes the advantage of ensemble learning. Instead of relying on a single decision tree, it constructs a multitude of decision trees at training time and outputs the mean prediction of the individual trees as the regression result. Due to the flexibility of the random forest model for both classification and regression applications, and the ability to handle overfitting and missing value problems, it has been successfully applied to many fields (Belgiu and Drăguţ, 2016; Chen et al., 2018; Pal, 2005). We implemented the random forest algorithm by the "randomforest" package (Liaw and Wiener, 2002) in R v3.6.3. In the random forest model, in addition to the variable stand density, which is directly related to the volume growth metric we were using, forest productivity was estimated only by phenometrics. Stand density was again treated as a categorical variable in the random forest model, and the records from the low silvicultural plots at RW20 sites were again removed.

Three metrics were used to measure the importance of variables in the fitted random forest regression model: the increment of mean squared error (MSE) when excluding a variable, the increment of node purity when splitting on a variable, and the variable depth in the decision trees. MSE is commonly used in assessing the model's prediction performance, the larger a variable change the MSE of a model, the more important the variable is. Node purity is measuring the splitting choice on a variable in the decision tree, the higher the purity increases when using a variable to split the tree, the more important the variable is. As for variable depth, the lower mean depths indicate variables that partition the data into more homogeneous subgroups, and are therefore, in a particular sense, more important to predicting the response. In addition, although the random forest algorithm embeds cross-validation in its decision tree building process, to evaluate how well the model performed on out-of-bag data (i.e. data that are not used in the model training process), we randomly sampled 70% of our data as the training data set to build the random forest regression model, and used the other 30% as the testing data to evaluate the model's predicting performance. This sampling and testing process were performed 1000 times to quantify the uncertainty.

3. Results

3.1. EVI2 time series

Plots subjected to high silvicultural treatments maintained greater dormant season EVI2 values, but maximum EVI2 values differed across sites (Fig. 5 a, b, Table 1, and Fig. 6). At RW19 sites, high silvicultural plots had higher EVI2 values during all growing seasons, whereas at RW20 sites, only dormant season EVI2 values corresponded to silviculture intensity, the relationship reversed at maximum EVI2 values. At RW20 sites in the summer, the EVI2 values of low silvicultural plots were equal to or higher than that of high silvicultural plots.

Stand density did not have a consistent and significant effect on the EVI2 time series across both RW19 and RW20 sites (Fig. 5 c, d and Table 1). When comparing the EVI2 time series between RW20 and RW19 sites where stand density was the same (1235 trees ha^{-1}), the RW20 sites had a higher magnitude of EVI2 values than the RW19 sites across most dates (Fig. 5 c, d).

As for the timing of phenology change, for RW20 sites, Greenup, MidGreenup, Maturity, and Senescence were significantly different between low and high silvicultural plots. While RW19 sites didn't suggest the same result (Table 1, Fig. 6). Likewise, no significant effect of density on the timing of phenology was found at RW19 and RW20 sites (Table 1).

Table 1
Significance test by repeated measures ANOVA. P-values < 0.01, which indicate highly significant, were marked in bold.

	P-value (Silviculture, including low and high levels)		P-value (Density, including 247, 494, 618, 741, 1235, and 1853 stems ha^{-1})	
	RW20	RW19	RW20	RW19
Greenup	**< 0.01**	0.65	0.41	0.03
MidGreenup	**< 0.01**	0.18	0.34	0.40
Maturity	**< 0.01**	0.38	0.29	0.89
Senescence	**< 0.01**	0.51	0.25	0.64
MidGreendown	0.90	0.96	0.10	0.12
Dormancy	0.63	0.43	0.14	0.28
EVI2min	**< 0.01**	**< 0.01**	0.08	0.16
EVI2max	**< 0.01**	**< 0.01**	0.58	**< 0.01**
EVI2area	0.3	0.15	0.28	0.03

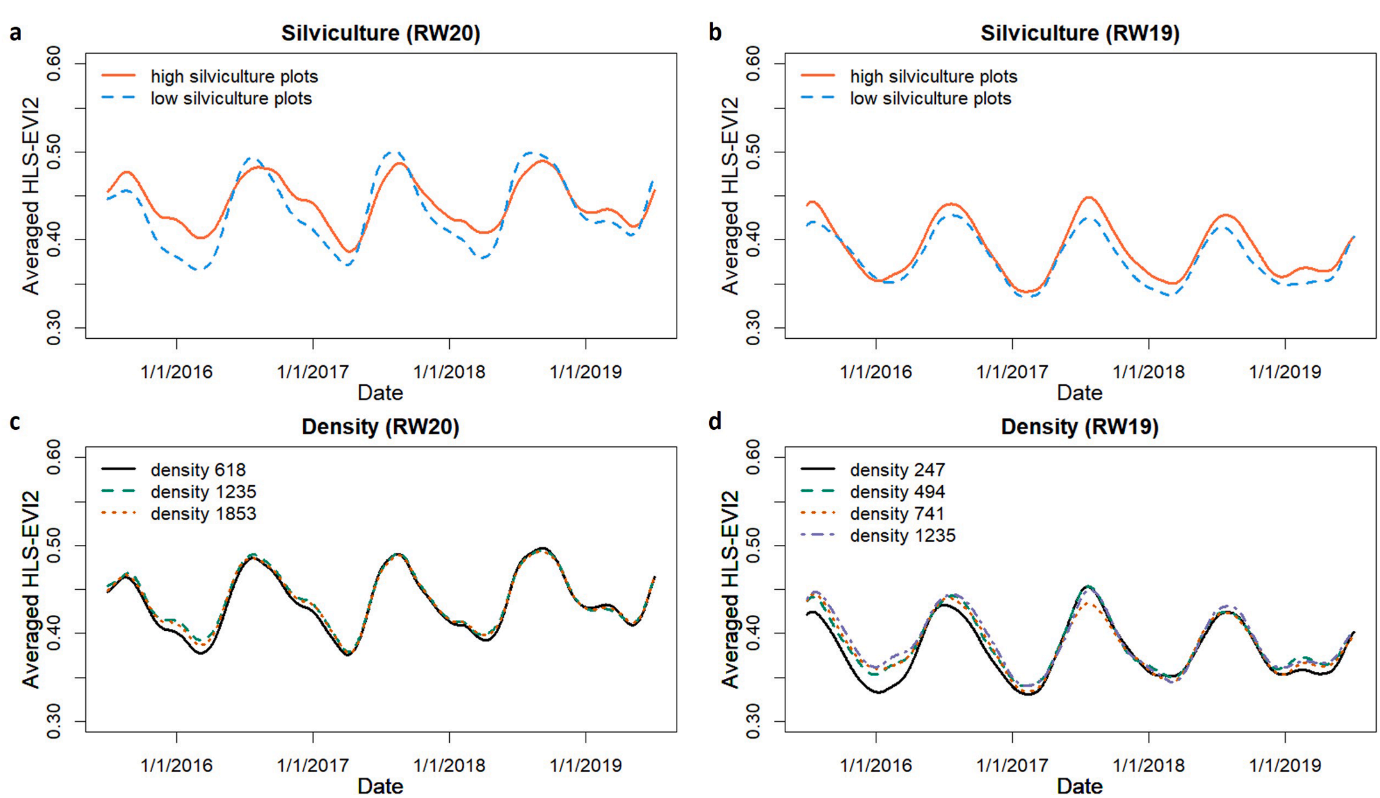

Fig. 5. EVI2 time series averaged by silviculture intensity and density levels. Treatment methods in RW20 and RW19 sites were described in Section 2.1.1. All subfigures have the same range of x and y axis.

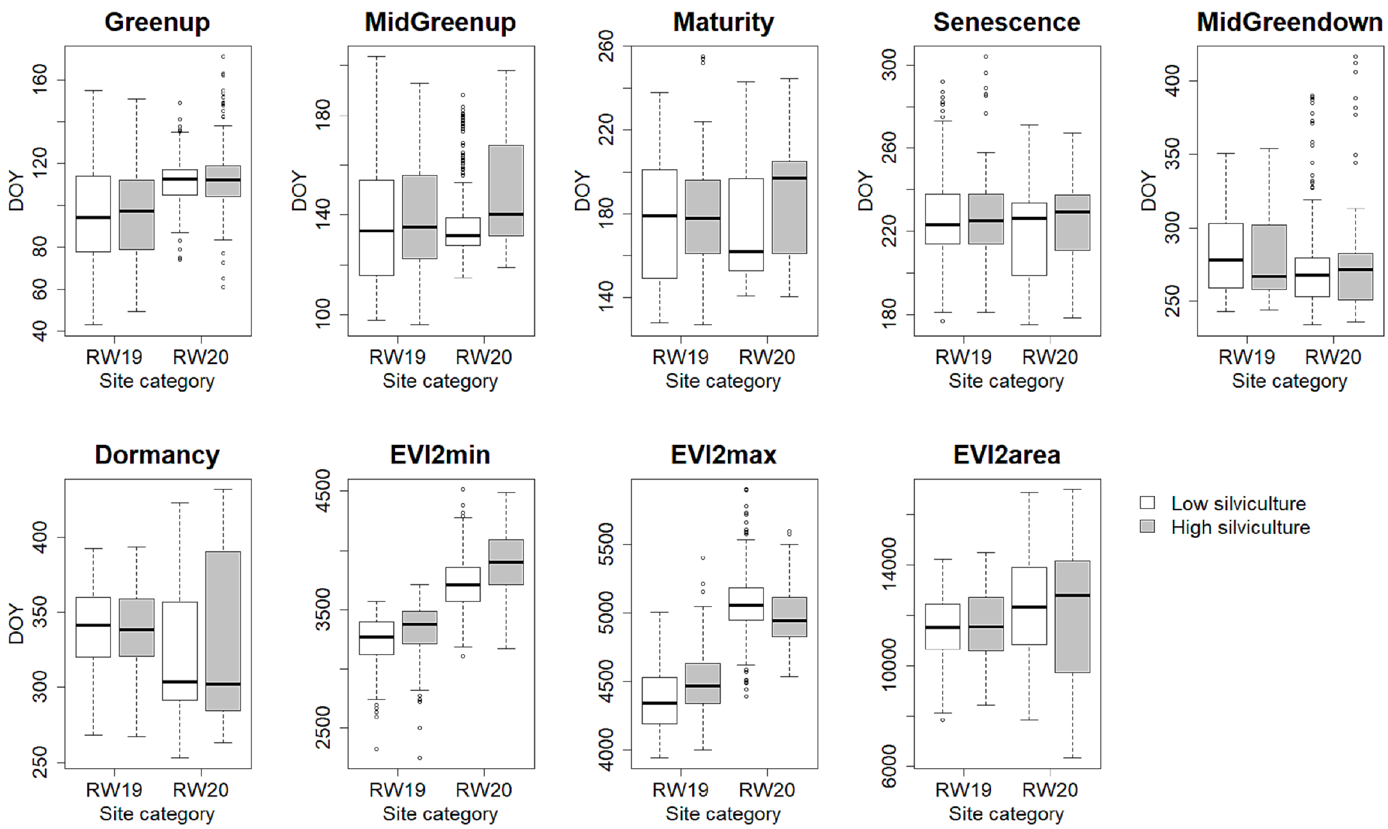

Fig. 6. Boxplots of phenometrics and EVI2 metrics at low and high silviculture levels for RW19 and RW20 sites.

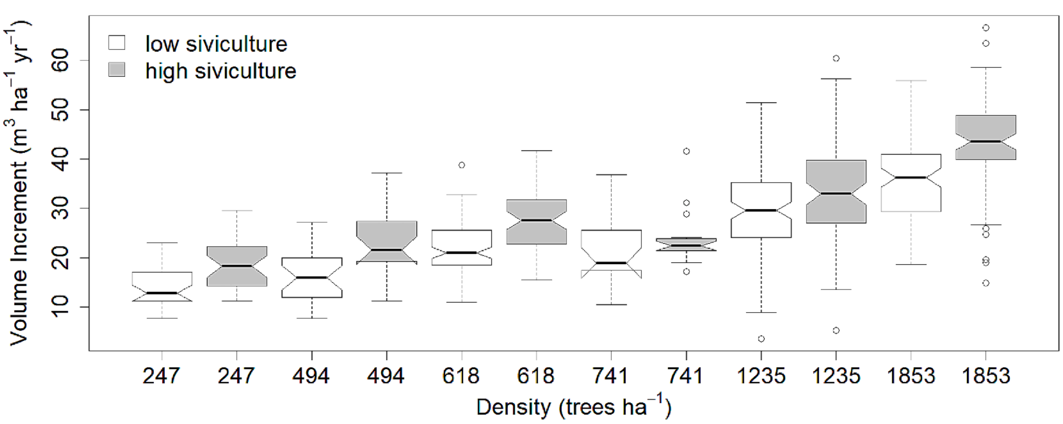

Fig. 7. Volume increment among silviculture and density levels. RW19 sites contain density levels of 247, 494, 741, and 1235 trees ha^{-1}; RW20 sites contain density level of 618, 1235, and 1853 trees ha^{-1}. The shape of notched boxplot of density 741 trees ha^{-1} was probably caused by relatively low sample size.

3.2. Volume growth model analysis

Greater density level tends to have greater annual volume increment per unit area for both high and low silviculture treatments (Fig. 7), although it does not mean individual trees in higher density level plots have greater annual volume increment than trees in lower density level plots. Silviculture and stand density were significant predictors with positive coefficients in the multiple linear regression model (Fig. 8).

In the linear model, the phenometrics EVI2min and EVI2max were significantly positively related to volume growth (Fig. 8), which means higher EVI2 values in dormant season (EVI2min) and growing season (EVI2max) were associated with greater volume growth. However, the model shows significant negative relationship between the integral of EVI2 during the growing season (EVI2area) and stand volume growth. Among the dates, Greenup and Maturity significantly related to volume growth with Greenup showing a negative relationship with volume growth, and Maturity showing a positive relationship. This result suggests that earlier Greenup dates and later Maturity dates which result in a longer green up season were associated with greater volume growth.

The cross validation of the random forest model performance had a mean R^2 value of 0.86 with a 95% confidence interval of 0.79 to 0.91 (p-value $<<$ 0.01) and RMSE value of 0.80 m^3 ha^{-1} yr^{-1} with a 95% confidence interval of 0.53 m^3 ha^{-1} yr^{-1} to 1.16 m^3 ha^{-1} yr^{-1} (Table 2), indicating that the random forest model can better express the relationship between stand volume increment and phenometrics than the multiple linear regression model, and suggesting that the relationship is likely non-linear. The performance of the random forest model suggests that phenometrics have great potential in estimating annual unit area

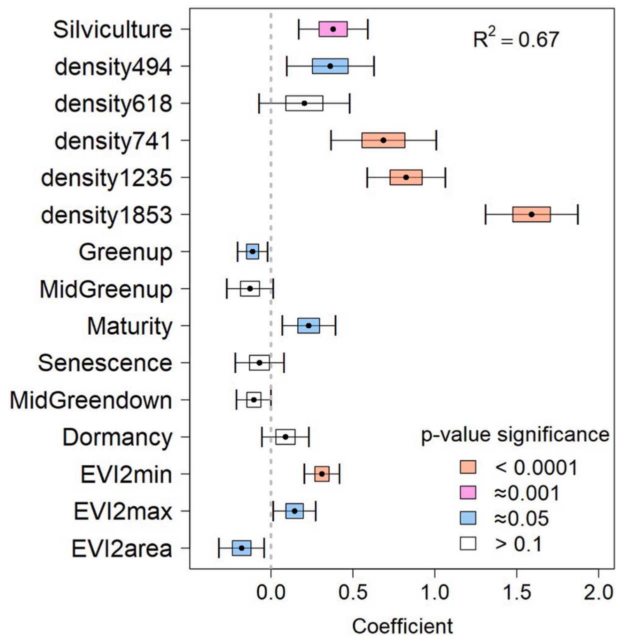

Fig. 8. The significance of multiple linear regression coefficients. Black dots are the mean estimated values for coefficients, while bars and rectangles are 95% confidence intervals and 50% confidence intervals, respectively,

Table 2
Cross validation result of the random forest model. The regression statistics were computed by linear regression between model predicted volume increment (m^3 ha^{-1} yr^{-1}) and field measured volume increment (m^3 ha^{-1} yr^{-1}).

	Mean	95% confidence interval
Slope	1.12	(1.03, 1.21)
Intercept	-3.54	(-5.79, -1.03)
R^2	0.86	(0.79, 0.91)
RMSE	0.80	(0.53, 1.16)
p-value	4.87×10^{-35}	(4.56×10^{-58}, 1.44×10^{-37})

volume growth.

The variable depth in Fig. 9a along with MSE and node purity metrics in Fig. 9b indicate that dormant season EVI2 (EVI2min) and peak season EVI2 (EVI2max) are important to estimate annual volume growth, and EVI2min is relatively more important than EVI2max, which is consistent with the multiple linear regression model.

4. Discussion

4.1. Phenology, silviculture, and productivity

We found a relationship between EVI2 measured phenology and volume growth in managed pine stands in the southeastern US. Specifically, volume growth increased with a longer green up season, which is defined as the period between Greenup and Maturity dates. The relationship between phenology and volume growth was likely to be non-linear as the random forest model better expressed the variability of volume growth than the multiple linear regression, even though silviculture levels were not included in the random forest model. Although land surface phenology has been used as an indicator of carbon uptake in forest ecosystems (Keenan et al., 2014), few studies have directly related volume growth with phenology at the stand scale due to limitations in spatial resolution of LSP products. Clearly, the newly developed 30 m spatial resolution LSP product has improved our ability to measure phenology at the stand scale. Volume growth is related to intercepted radiation (e.g. Cannell, 1989), and light interception increases with increasing leaf area index (LAI) (e.g. Vose and Allen, 1988) in loblolly pine. A relationship between volume growth and intercepted light for the RW20 sites has been reported (Albaugh et al., 2018), where volume growth per unit absorbed light increased with increasing stand density. This result was similar to our findings where stand density was a significant predictor variable of volume growth in the linear model, and similarly important in the random forest model.

That volume growth was related to longer green up periods is consistent with the recent finding by field experiments where phenology was documented by digital repeat photography (Luo et al., 2020), and may be related to the hypothesis proposed by (Sampson et al., 2001) who found that current year growth was not supported by current photosynthate but relied on stored carbohydrates to meet carbon demand early in the season. Carbon can be fixed during the dormant

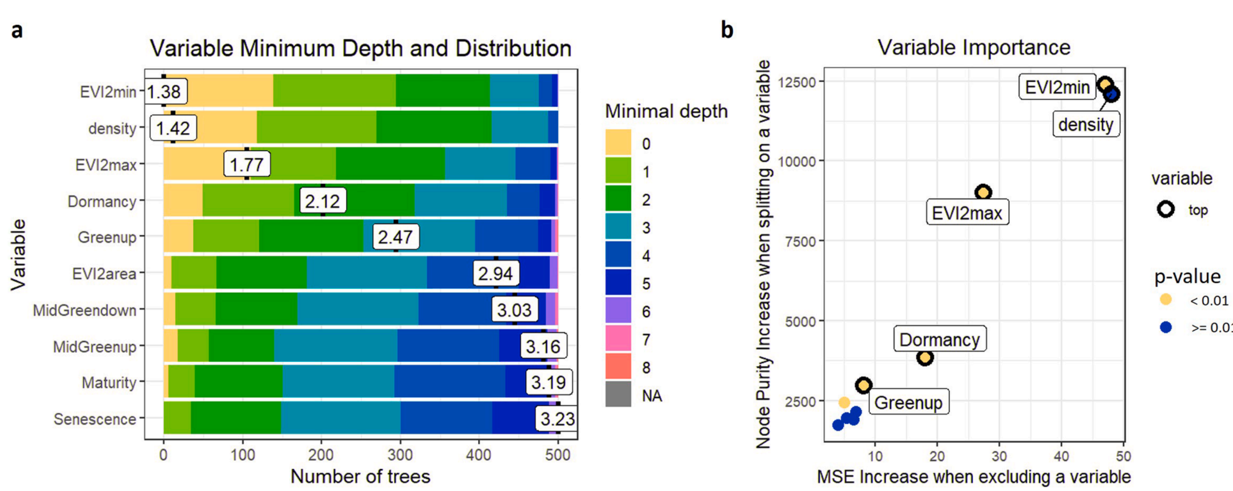

Fig. 9. Variable importance of the random forest model. a) Distribution of minimal and mean depth of each variable in the decision trees. Bars and labels in each row represent the mean depth. X-axis indicates the number of decision trees containing the variable and y-axis indicates variable names. In this case, 500 decision trees were built and all variables were used in each decision tree; b) Variable importance plot of MSE increases when excluding a variable vs. node purity increases when splitting on a variable. The variables had MSE increase less than 10 and node purity increase less than 2500 were EVI2area (p-value < 0.01), MidGreendown, MidGreenup, Maturity, and Senescence.

season under favorable conditions (temperatures > 5 degrees C), yet little volume growth occurs at this time and the carbon is stored as labile carbohydrates. A large store of these carbohydrates available during the green up period may explain why this EVI2 measured time is so important to predicting volume growth.

We also found that volume growth was associated with winter values (EVI2min) (Figs. 8 and 9) where higher winter values were associated with greater volume growth. EVI2 reflects the amount and activity (photosynthesis) of leaves. Trees with more active foliage during the winter would be able to produce and store more labile carbohydrates than trees with less foliage. Consequently, trees with more foliage in the winter will likely have more stored carbohydrates, that may become available to meet growth demands when current photosynthate is insufficient during the green up period. If so, it adds further support to the Sampson et al. (2001) hypothesis as stated earlier.

Fertilization of nutrient-limited stands increases LAI and ultimately increases volume production (e.g. Albaugh et al., 1998). At the RW19 sites, fertilization resulted in higher EVI2 values throughout the year (Fig. 5b), however, fertilization at the RW20 sites resulted in a situation where EVI2 values were higher in the high silvicultural plots in the winter but lower in the summer when compared to low silvicultural plots (Fig. 5a). It is likely that these differences were a result of the competition control practices applied in the two studies. In the RW19 sites, all plots (both fertilized and unfertilized) received operational competition control after thinning. Consequently, the competing vegetation populations were likely at relatively the same low levels across all plots so the differences detected by EVI2 measurements would be due solely to fertilization and would be visible throughout the year as measured with EVI2 data. At the RW20 sites, high silvicultural plots receiving intensive fertilization also received high levels of competition control such that there was very little competing vegetation in the fertilized plots. However, the plots that did not receive fertilization only received competition control at planting and had large populations of mostly deciduous competing vegetation. During the winter, when the deciduous competing vegetation was dormant and had no leaves, the high silvicultural plots had higher EVI2 values than the low silvicultural plots. But the reverse was true in the summer when the deciduous vegetation leafed out. It appears the EVI2 metric is quite sensitive to foliage display in that we were able to detect these differences. Nonetheless, this effect could be problematic if one were only interested in a particular species (crop or otherwise). The issue is similar to the difficulties encountered when measuring LAI remotely (Blinn et al., 2012). EVI2 data should be able to distinguish between evergreen and deciduous species with time series data as done here and similar to those procedures used when measuring LAI (Blinn et al., 2012). However, measurement where the species of interest and other species are the same type (deciduous or evergreen) will likely require additional work to distinguish between the different species.

For a given study, differences in stand density whether achieved at planting or with thinning were not detected by EVI2 metrics. This result may be related to the timing of our EVI2 measurements relative to stand development. For both studies, our EVI2 measurements were some years after the stand density management treatment (planting in RW20 or thinning in the RW19) was applied. During the intervening time period, the crowns on all trees would be expanding to fill the open space in the canopy. Given the length of time after treatment and at the stand density levels observed here, canopy closure or near canopy closure had likely occurred in all treatments. In the RW20, this effect has been quantified where the lower stand density treatments have trees with large branches low in the canopy that largely create a closed canopy (Albaugh et al., 2019).

The silvicultural treatments (fertilization, density management) imposed in our studies did influence volume growth as noted in the multiple linear regression model. But even though there were significant fertilization effects on the EVI2 time series, we did not find evidence suggesting that the silvicultural treatments directly influenced the EVI2 phenology metrics (Table 1). In studies examining loblolly pine foliage phenology, fertilization could affect the size and number of fascicles but did not influence the overall pattern of foliage display and longevity (Albaugh et al., 2010). If this phenomenon was the case in our studies where fertilizer increased the foliage amount but not the foliage display, we could have observed an increase in the maximum EVI2 metric but would not expect to observe differences in metrics related to display (Area). Other studies have found site specific increases in growing season length attributed to improved nitrogen availability (Xi et al., 2015). As noted, EVI2 data combines information on foliage amount and activity (photosynthesis). Other studies have shown that fertilization does not increase photosynthetic capacity over the long term (Gough et al., 2004). Data from the RW20 sites did show statistically different effects on maximum photosynthesis due to silvicultural intensity for some measurement periods at the North Carolina RW20 site which were small in magnitude and the opposite of what one might expect where the low silviculture plots (no fertilization) had higher maximum photosynthetic rates than the high silviculture plots (Yáñez et al., 2017, p.). No differences in photosynthetic rates were observed at the Virginia RW20 site in the Yáñez et al. (2017) study. The combination of these factors (fertilization affects foliage amount but not display and has small or no effect on photosynthesis) likely resulted in the lack of a direct effect of fertilization on EVI2 phenology metrics. Similarly, stand density did not directly affect EVI2 phenology metrics. Density management allocates site resources to a different number of individuals in the stand. After a time, a low density stand could have a similar amount of foliage mass as a high density stand, although it would be allocated over fewer individuals. Photosynthetic rates do not increase overall in thinned stands, although foliage located lower (closer to the ground) in the crown of residual trees in thinned stands do have higher photosynthetic rates than corresponding foliage in trees where no thinning occurred (Peterson et al., 1997). These factors make it unlikely that stand density differences in our stands would have directly influenced EVI2 metrics.

4.2. Competing vegetation effects

As noted earlier, competing vegetation played an important role in the observed EVI2 metrics. Our phenometrics were generated from the combination of crop species (pine) and competing vegetation (everything else) in the measured stands. If we ignored (or were unaware of) this effect on EVI2 signals, our conclusions about the relationship between phenology, treatments, and productivity would be in error. For example, at RW20 sites, ignoring competing vegetation effects on EVI2 signals would lead us to conclude that fertilization increased dormant EVI2 values but decreased maximum EVI2 values. Although the competing vegetation effect on the amplitude of EVI2 values might be relatively small, this effect could be amplified when being aggregated into coarse remotely sensed image pixels. For example, in coarse spatial resolution images, spring phenology could be dominated by vegetation with relatively early Greenup dates. Likewise, in the autumn, the remotely sensed phenometrics could be dominated by vegetation that has relatively late Senescence dates (Peng et al., 2017; Zhang et al., 2017). If the competing vegetation has early spring Greenup and or later Senescence dates relative to the crop species, the remotely sensed growing season length would be overestimated. If these incorrect interpretations were then used in other analyses concerning, for example, the carbon cycle of the crop species, it is likely we might overestimate how productive the crop species would be in response to climate change. Recent studies have shown that competing vegetation could cause discrepancies between in situ observations and remotely sensed phenology data in the autumn and alter GPP and NEE estimates (Donnelly et al., 2018; Donnelly et al., 2019; Zhao et al., 2020). Similarly, each species of competing vegetation will likely have its own response to climate change that further affects the observed phenometrics. Moreover, the competing vegetation effect would be difficult to quantify remotely when investigating forests with both deciduous crop trees and deciduous competing vegetation. It would be challenging to separate their relative timing of leaf development and senescence from remotely sensed observations. There would be a similar problem when both the crop species and competing vegetation were evergreen. In the final analysis, any use of EVI2 phenometrics requires a good understanding of the vegetation dynamics of the studied area.

4.3. Limitations

Our study has some limitations. 1) The field experiment data are limited. The field experiments were conducted across the southeastern US, accounting for different types of climatic environments, however the variation of fertilization intensity is limited. Thus, instead of investigating the impacts of different intensities of fertilization on phenology, we could only treat the fertilization data as categorical. Although we found that fertilization elevated EVI2 time series in the growing season, the impacts of fertilization on phenological dates need further investigation. At the same time, our range of fertilization did cover the likely range of what would be applied (our treatments included no fertilization and sufficient fertilizer to prevent any nutrient deficiencies) and, consequently, whereas additional levels of fertilization and the information of nutrients naturally in the soil would be useful, we have likely covered the range of response. 2) The field experiment designs were different for the RW19 and RW20 studies as they were designed to meet different objectives. Although the long-term field experiments provided a great resource of volume growth records, they were implemented in different years and their study purposes varied, i.e., RW19 and RW20 treatments were not exactly the same. For example, the RW20 studies were treated from planting, whereas the RW19 studies were treated at mid-rotation when the trees were between 12 and 16 years old. 3) The study was made on trees with rather closed canopies. At locations where trees are younger or have less canopies, we would expect that the competing vegetation would have even more influence on the remotely sensed EVI2 signals, making it more difficult to conduct the analysis. 4) The scale limitation of the LSP product. Even though the HLS-LSP product improved the spatial scale of LSP to 30 m so that the scale can match the size of field experimental plots, allowing us to investigate the relationship between LSP and forest productivity. Higher spatial resolution LSP imagery would further reduce uncertainty caused by mixed pixel effect and improve our ability to investigate additional phenomena.

There are many methods that can be used to retrieve phenometrics. In this study, we retrieved phenometrics using 15%, 50%, 90% of EVI2 amplitude to represent Greenup, MidGreenup, Maturity in the spring, and Senescence, MidGreendown, Dormancy in the autumn. Although the LSP retrieval methodology has been validated with ground observed phenology datasets (Bolton et al., 2020), ground observations, which would help us better understand the ecological meaning of the LSP, were unavailable for our study sites. Those insights may improve our understanding of the physical processes that link phenology and productivity, and point towards further model improvement. Other methods include retrieving phenometrics based on various vegetation indices (Delbart et al., 2005; Hmimina et al., 2013; Karkauskaite et al., 2017; Sakamoto et al., 2005; Zhu et al., 2012), transforming the time series of vegetation indices using logistic functions (Cao et al., 2015; Zhang et al., 2003), and selecting various thresholds to represent phenometrics (You et al., 2013). Although the specific phenometrics derived (e.g. specific dates for Greenup and other variables measured here) might vary depending on the method used, the seasonal photosynthesis mechanism that affects productivity should be robust. In addition, at the time this study was conducted, the Peak layer, representing the date when EVI2 value reaches the maximum point, in the HLS-LSP product was not available, thus we did not include it in the analysis.

5. Conclusion

We investigated the relationship between phenology, silvicultural treatments, and forest productivity of managed pine stands in the southeastern US by utilizing a new 30 m land surface phenology dataset and field experiment measurements. We fitted a multiple linear regression model that found greater volume growth associated with a longer Greenup season, which is defined by the period between the green up and maturity dates. Fertilization resulted in higher EVI2 values throughout the year and this increase in EVI2 values was especially noticeable at some sites during the winter. Despite the increase in EVI2 values as a result of fertilization, no direct effects of silvicultural treatment on EVI2 phenological dates were found in this study. The random forest model was used as well and corroborated the results found with multiple linear regression. The cross validation with R^2 value of 0.86 and RMSE value of 0.8 $m^3\ ha^{-1}\ yr^{-1}$ suggests that phenometrics are good indicators of stand productivity. Our EVI2 time series of controlled field experiments from HLS imagery found that competing vegetation could affect remotely sensed observations and should be paid special attention. While finer spatial resolution (< 30 m) LSP observations are still necessary to provide more variabilities of phenometrics, our findings can help better understand the impacts of future climate change on forest productivity and ecosystem carbon dynamics.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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