Understanding the internal and external driving factors that impact specific gravity in Longleaf Pine through a spatial and temporal perspective

by

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Keywords: specific gravity (SG), Pinus palustris, carbon, randomForest, geographically weighted regression, radial pattern

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Abstract

Specific gravity (SG, also called relative density) is a dimensionless quantity defined as the ratio of a substance's density (mass per unit volume) to the density of a given reference material. In forestry, wood SG is often measured as the ratio of the mass of wood of a unit volume to water at a given temperature of 4 °C. It is a critical factor in estimating tree carbon storage. This study aims to identify the key environmental variables influencing the SG of longleaf pine (*Pinus palustris*), examine their interactions, and explore regional variations in SG across its native southern range. Additionally, anthropogenic climate change altering weather patterns may drastically impact carbon storage because carbon storage heavily relies on available moisture. Additionally, past the ring count of 62, there is very little information on how carbon is stored in high ring count trees. Therefore, we must understand how ring count and climate, with their interactions, affect carbon storage from a temporal perspective. This study attempts to understand how different climate variables (PDSI, precipitation, temperature, and vapor pressure deficit) and soil (available water capacity, sand, silt, clay, and organic matter) impact wood specific gravity. Our main finding was a strong negative relationship between SG and ring count after year 62. We also found that both precipitation and very coarse particles had a positive relationship with SG. We found negative relationships between SG and spring precipitation, annual maximum temperature, coarse sand, and organic matter. Additionally, we found one positive relationship with rainfall during June through December. We also identified the interactions between spring precipitation, precipitation between June and December, annual maximum temperature, available water capacity, and sand. For the local coefficients in the GWR, we found that most of the spatial distribution aligned with our global coefficient.

However, there were specific locations within each factor where the relationship with SG remained unexplained.

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Chapter 1.

Regional variations of specific gravity of longleaf pine (*Pinus palustris)* and driving factors

1.0 Abstract

Specific gravity (SG, also called relative density) is a dimensionless quantity defined as the ratio of a substance's density (mass of a unit volume) to the density of a given reference material. In forestry, wood SG is often measured as the ratio of the mass of wood of a unit volume to water at a given temperature of 4 °C. It is a critical factor to estimate tree carbon storage accurately. This study aims to identify the key environmental variables influencing the SG of longleaf pine (*Pinus palustris*), examine their interactions, and explore regional variations in SG across its native southern range. We collected 153 cores from various locations across Alabama, Mississippi, Georgia, and Florida. SG was estimated by segmenting the cores into 5-year intervals to calculate a weighted average, with measurements taken using physical methods. The environmental factors, including climate (precipitation, temperature, and vapor pressure deficit) and soil properties (available water capacity, sand, clay, silt, and organic matter), were obtained from open-source datasets. Random Forest and regression tree models were employed to assess the relative importance and interactions between variables. Additionally, Geographically Weighted Regression (GWR) was used to examine local correlations.

We found negative relationships between SG and spring precipitation, annual maximum temperature, coarse sand, and organic matter. Additionally, we found one positive relationship with rainfall during June through December. We also identified the interactions between spring precipitation, precipitation between June and December, annual maximum temperature, available water capacity, and sand. For the local coefficients in the GWR, we found that most of the spatial

distribution aligned with our global coefficient. However, there were specific locations within each factor where the relationship with SG remained unexplained. Therefore, more research is needed to investigate what causes these unexpected relationships with SG. We hope these results highlight the importance of SG values that extend beyond species-specific data. Additionally, we aim for this information to enhance the accuracy of carbon markets by better understanding the spatial distribution of carbon and the environmental factors driving its allocation. Finally, we hope this study will inform decision-making on planting Longleaf Pine for carbon market purposes.

Keywords: specific gravity (SG), Pinus palustris, randomForest, regression tree, geographically weighted regression.

1.1 Introduction

A forest stand or a tree's carbon storage is usually estimated by measuring above-ground biomass. Destructive sampling, such as stem analysis, has been the standard method for estimating above-ground biomass of trees. Although accurate, this sampling technique is often costly and time-consuming (Weiskittel et al., 2015). With the advancement of new technologies, researchers are increasingly exploring non-destructive methods for estimating biomass, such as LiDAR-based biomass mapping and terrestrial laser scanning (Velasco & Chen, 2019; Wilkes et al., 2018; Stovall et al., 2017). A commonly used approach involves applying published species-specific gravity (SG) values—known as wood density—to convert mapped or scanned wood volume into biomass. However, the commonly used SG values for this conversion (Miles & Smith, 2009) have been criticized for potential bias, as they are species-specific and fail to account for other environmental factors within the species that influence variation in wood SG (Weiskittel et al., 2015). This inaccuracy has been documented in studies such as Arsenious (2023), who compared two biomass estimates from 3D volume models generated using terrestrial LiDAR. One estimate used species-specific SG values from Miles and Smith (2009), while the other used true SG values obtained through destructive sampling of the same tree. The study found that biomass estimates based on published SG values were less accurate than those using directly measured SG. These findings stress the importance of quantifying intra-specific factors that influence SG as a foundational step toward developing more accurate SG values for carbon estimation and improving our understanding of carbon storage.

Multiple internal biological systems regulate wood SG and affect carbon sequestration and stock; the most notable is the ratio of latewood to earlywood (Zobel and Buijtenen, 1989). For the southern pines, a moderate correlation coefficient (r = 0.54) was found between latewood percentage and SG core for Loblolly pine (*Pinus tadea*) and Slash pine (*Pinus elliottii*) (Gilmore et al., 1966). This correlation is consistent with findings for longleaf pine, where the SG of latewood has been reported to be 2.46 times higher than that of earlywood (Paul & Smith, 1963), as latewood is characterized by its small lumen and thick cell walls (Speer et al., 2010). Understanding the factors that regulate latewood formation may therefore provide critical insights into the drivers of wood specific gravity and enhance our ability to understand SG spatial variation.

Several studies have directly linked climate to variation in specific gravity (SG). For instance, one study found that southern pines in Florida exhibit higher SG than their inland and northern counterparts. This difference is attributed to an extended latewood growth period, driven by the region's heavy late-summer rainfall. Another study reported that loblolly pine

(*Pinus taeda*) exhibited notably low SG when grown under conditions with sufficient spring rainfall but limited precipitation during the summer and early fall. This was caused by the lack of latewood in the annual rings due to the minimal precipitation during its growing months of summer and early fall (Zobel and Buijtenen, 1989).

Latewood growth in longleaf pine is highly sensitive to climatic variability. Stambaugh et al. (2021) reported a strong positive correlation between latewood growth and the Palmer Drought Z-Index in the Southern Georgia region from June to October. These findings indicate that latewood production decreases during drought and increases during wetter conditions, highlighting the influence of moisture availability on wood formation dynamics. Soule et al. (2021) found that July through September precipitation positively correlated with latewood adjusted radial growth in the Coastal Plan of North and South Carolina. Henderson et al. (2009) identified the strongest seasonal correlation with latewood growth as a positive relationship during the summer months (June–August) at sites in Texas and North Carolina. Zampieri et al. (2024) found a negative correlation with late summer temperature and a positive correlation with early summer precipitation to latewood growth. Although earlywood may impact specific gravity (SG), its width does not vary as much as latewood, suggesting that earlywood deposition is more genetically controlled than latewood (Harley et al., 2023; Cosgrove, 2000).

For soils, the larger diameter soil particles, such as sand, allow water to drain through more easily and hold water in the soil for a shorter period. For smaller diameter particles, such as clay, the water cannot drain through as quickly; therefore, the water is available to the plant for a longer period. With this logic, soil may play a crucial role in determining available moisture and changes based on its spatial location; therefore, it has the potential to influence SG. Additionally, the available water capacity (cm/cm) will be tested against soil gravity, as it quantifies the amount of water the soil can store for plant uptake. Furthermore, the amount of organic matter in the soil may also impact the SG. A study compared the Longleaf wood SG between cutover sites and old agricultural fields and found that the agricultural field sites had a lower SG. They attributed this difference to the agricultural field's residual fertilizer (Raut et al., 2021). A study on loblolly pine found that fertilization had also lowered the SG (Love-Myers et al., 2010). It is believed that the fertilizer was able to lower the SG due to the increase in available nutrients. For this reason, the percentage of organic matter in the soil will be tested in relation to the soil's grain size, as it contains valuable nutrients essential for plant growth.

It is important to note that the studies referenced above were conducted across different geographic locations and used varying timeframes to examine the relationship between climate and specific gravity (SG). The precise timing of latewood formation remains poorly understood, as it can vary depending on both species and site-specific environmental conditions. To our knowledge, only one study has precisely documented the timing of the latewood production period in Longleaf pine. Rother et al. (2018) examined growth patterns at two primary sites in Florida: Avon Park and the Buffer Preserve. An equal number of longleaf pine and slash pine (*Pinus elliottii*) trees were sampled at each site. At the Avon Park site, earlywood production was observed from February to May, with a transition to latewood beginning in June. Latewood formation continued from July through December, followed by a period of dormancy in January. At the Buffer Preserve site, a similar growth pattern was observed; however, February marked a period of dormancy, with earlywood production commencing in March. Additionally, the study noted that some trees exhibited no dormant period, with smaller trees less likely to enter dormancy than larger trees. This study demonstrated that the production of earlywood and latewood—and consequently, a tree's specific gravity (SG)—may vary depending on species, size, and location.

There is evidence that a spatial pattern exists for longleaf pine SG, as it has been recorded that SG is higher in the south and near the coast, but lower in the north and inland areas (Zobel et al., 1972). Yet, the exact cause of this distribution is not well understood. However, previous studies examining the relationship between SG and precipitation and dendrochronology studies on seasonwood growth suggest that climate, or more specifically, available moisture during the latewood growing season, is the primary factor affecting SG. The concept that available moisture influences specific gravity (SG) is not novel, as previously noted by Zobel and Buijtenen (1989). Therefore, in addition to precipitation, temperature, and soil properties will be included in this study as well. This chapter aims to answer the following two questions:

1. What important variables contribute to the SG of longleaf pine, and how do they interact with each other to affect the change of SG?
2. How does the longleaf pine's SG change with these factors regionally?

Understanding the factors that influence the spatial distribution of specific gravity (SG) in longleaf pine is critical for informing strategic planning decisions, particularly when cultivating the species for participation in carbon markets. Moreover, this knowledge enhances our understanding of carbon storage patterns, offering insight into why certain areas accumulate more carbon than others- an essential consideration for accurately allocating carbon credits and optimizing market effectiveness.

1. 2 Methods

1.2.1 Study Sites and environmental variables used

The study sites are located across northern and central Florida, southwestern Georgia, southern Alabama, and southeastern Mississippi, within the native range of longleaf pine (Figure 1). The interpolated annual precipitation from 1895 to 2023 for all study sites ranged from 733.79 to 2,693.37 mm for an average of 1,475 mm. The minimum annual temperature ranged from 9.6°C to 19.3°C with an average of 14.1°C. The maximum annual temperature ranged from 22.9 °C to 31.1 °C with an average of 26.2 °C. The annual minimum vapor deficit pressure ranged from .07 hPa to 2.77 hPa with an average of .87 hPa. The annual maximum vapor deficit pressure ranged from 11.89 hPa to 25.5 hPa with an average of 17.9 hPa (The PRISM Climate Group, 2025).

The soil varies in texture and organic matter. Specifically, the total amount of sand in each soil ranged from 27.4% to 98.0% with an average of 77.4%. The total amount of silt in each soil ranged from 1.0% to 35.4% with an average of 11.5%. The total amount of clay in each soil ranges from .9% to 37.2% with an average of 11.0%. The total amount of organic matter found in each soil ranged from 0.1 % to 2.9 % with an average of 0.5 %. Additionally, the total available water capacity for each soil ranged from .04 cm/cm to .17 cm/cm with an average of .098 cm/cm. All this information was provided by the Web Soil Survey (Soil Survey Staff).

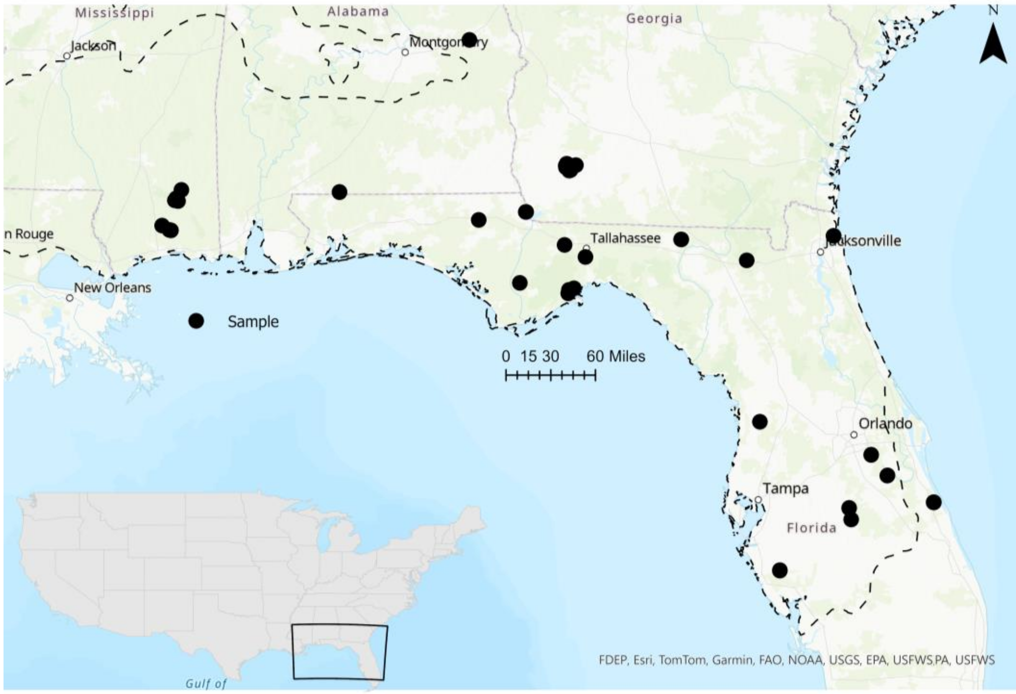


Figure 1. Map of study sites where wood cores were collected at the breast height of stems to measure the specific gravity of longleaf pine.

The monthly and annual precipitation (mm), temperature (C), vapor pressure deficit (hPa), and temperature dewpoint (C) were obtained from PRISM (AN81mdataset, https://prism.oregonstate.edu/) at 4km resolution (PRISM Climate Group, 2025). The annual and monthly Palmer Drought Severity Index (PDSI) from 1895 to 2024 was collected from the National Centers for Environmental Information (https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/county/mapping) at the county level (NOAA National Centers for Environmental Information, 2025). The soil data was collected from the Web Soil Survey provided by the United States Department of Agriculture (USDA) (Soil Survey Staff). The variables extracted from the dataset and used in this study are listed in Appendix 1 and 2. The variables were calculated using a weighted average of 0 cm (the top of the soil) to 200 cm depth.

1.2.2 Field sampling and SG measurement:

In total, 5, 17, 42, and 17 core samples were collected at the Tuskegee National Forest, Escambia Experimental Forest, De Soto National Forest, and the Jones Center. The samples were taken using a 12- and 10-mm increment borer at breast height (4.5 feet) during May through July of 2024. It should be noted that there is a slight overestimation of whole tree SG when using breast height cores for SG estimation because the vertical variation is not considered (Taras and Wahlgren, 1963). Yet, a majority of the literature uses breast height samples for SG estimation (Sauicer and Tara, 1969, Eberhardt et al., 2015, Eberhardt et al., 2018). Therefore, to be comparable to the literature and for the methodology to be accessible, we decided to use breast height cores for SG estimation.

A longleaf pine that stood straight and appeared visually healthy was chosen for sampling. The side with the least amount of compression wood, based on the canopy cover, was cored. Once the core is obtained, it is placed in a zipped plastic bag, kept on ice during transportation, and stored in a freezer until it is ready for processing. The samples were kept frozen to preserve as much moisture as possible, ensuring they remained at or above the fiber saturation point (30% moisture content (MC)) for accurate green volume measurements (Forest Products Laboratory, 1987). The equation to calculate moisture content is as follows,

$$MC = 100\left(\frac{wg - wd}{wd}\right) \qquad (1)$$

where *wg* and *wd* represent the green and oven-dried weight of core samples.

Our specific gravity methodology was developed in accordance with the guidelines provided by Williamson and Wiemann (2010). The SG was calculated using the following equation,

$$BSG = \frac{\frac{Ovendried\ Weight\ (g)}{Green\ Volume\ (mm^3)}}{.001g/mm^3} \tag{2}$$

where BSG stands for basic specific gravity (g/mm3). The oven-dried weight refers to the mass of the wood at a moisture content of 0%. Green volume is measured when the sample exceeds the fiber saturation point, which corresponds to a moisture content of 30% or higher. The density of water is approximately 1.000 g/cm³.

Before volume and weight estimation, the core samples were segmented into 5-ring intervals. Due to narrow rings, some ring segments would be too small to measure, which would compromise the data quality. Therefore, some samples contained segments of 10, 15, or even 20 rings. The cutting will be done using a general Xacto knife, tracing the latewood of the last ring to make the cut. Since a core sample was cut into multiple segments of 5 years or more (ring count), the SG of a core sample was calculated as the weighted mean of the SGs of all segments.

It is standard practice to record green volume and weight measurements immediately after sample collection to minimize moisture loss. However, due to the considerable distance between study sites and the large volume of samples collected simultaneously, immediate processing was not feasible. Therefore, all samples were frozen in the field to preserve the moisture for an accurate green volume estimation. To adhere to standard procedures, the samples would be thawed prior to measurement in the laboratory. To determine whether frozen samples could be reliably processed, we collected six 12-mm core samples and compared their weight and volume in both frozen and thawed states using a paired t-test. The test results did not show a significant difference between the frozen 12 mm volume and weight measurements and the 3-to-4-hour volume and weight measurements after the sample was thawed, indicating that the field procedures of core sample collection and processing were appropriate.

The diameter and length of core segments were measured using an electric caliper, and the volume was calculated using the cylinder formula. It should be noted that some samples were slanted (Figure 2), and to account for this, both heights were measured and averaged to use as the length. To measure the weight, the Mettler AE 200 scale was used. After the initial measurements were recorded, each sample was left out at room temperature (21.1°C). After 3 to 4 hours, the sample was measured again using the same procedure.

Figure 2.The slanted core segment (left) and the normal core segment (right) of 5 rings of longleaf pine.

Measuring Green Volume:

Originally, an infrared thermometer, commonly known as a temperature gun, would be used to determine when the sample was thawed, and measurements could be recorded. The infrared thermometer used was able to convert infrared radiation to temperature. The issue was that the infrared thermometer was only picking up the temperature of the surrounding air and not the temperature of the core itself. Without knowing its temperature, it is difficult to pick a time to determine when it has thawed, since if we waited too long, enough moisture may have evaporated, causing a change in weight and volume. However, the 3 to 4-hour timeframe was chosen based on USDA guidelines, which state that a 3- to 4-pound package of chicken can thaw in cold water within approximately 2 to 3 hours. Therefore, a 12 mm core should also be able to thaw and fully defrost within that time frame; however, an additional hour was included as a precaution to ensure complete thawing. We also conducted a 23-hour measurement, ensuring the core was completely thawed, thereby providing more robust evidence.

The results indicate that volume measurements taken after both 3–4 hours and 23 hours of thawing showed no significant difference compared to those obtained from frozen samples. This suggests that accurate volume measurements can be performed directly on frozen samples without prior thawing. The 3–4-hour weight measurements showed no significant difference compared to the frozen samples; however, the 23-hour measurements did exhibit a significant difference. This discrepancy in the 23-hour samples is likely due to moisture evaporation during the extended thawing period. Given the minimal difference in the 3–4-hour measurements, frozen samples can still be reliably used for weight assessments. When measuring green weight, the primary concern with using frozen instead of fresh samples is the potential decrease in weight due to evaporation. This decrease is not problematic, as it would only lead to an underestimation of the moisture content (MC), potentially suggesting that the sample is below the fiber saturation point when it is above. Therefore, we determined that frozen samples can be used to take green weight and volume.

For the 10 mm, they are all significantly different, except for the volume for 3 hours. This means the green volume can be accurately measured with the frozen sample, but the green weight cannot. We can still use the moisture content to determine if the sample is at a fiber saturation rate because the freezing will only lower the moisture content. Yet, we cannot rely on the moisture content to be accurate. Therefore, we will use the samples we took with the 10 mm borer to calculate SG, but for the future, we will only use the 12 mm borer.

Measuring Green Weight and Dry Weight

The frozen samples were used to measure the green weight of the samples. The green weight was measured for subsequent use in calculating moisture content (%). Moisture content is important because for volume estimation to be considered green volume, it needs to be at or higher than the fiber saturation point, which for most wood is 30% in moisture content or higher (Forest Products Laboratory, 1987). After segmentation, a small glass beaker was zeroed on the Mettler AE 200 scale, and the sample was placed into the beaker. After the first weight was recorded, to ensure accuracy, the process was repeated for a second weight measurement. Then, the two weight measurements were averaged, and this value was used to calculate moisture content (%).

After volume estimation, each core will be placed in its designated aluminum container, measuring 12.7 cm × 7.62 cm × 5.08 cm, for oven drying. The segments will be evenly spread within the container to ensure uniform drying. The samples will remain in the oven at 105°C for 24 to 72 hours to ensure complete moisture evaporation (Williamson and Wiemann, 2010). After 24 hours, the four largest samples will be selected and weighed. These same four samples will be reweighed at intervals of 24 hours or more to monitor changes in mass. This process will continue until the difference between consecutive measurements is less than 0.001 grams. For the SG calculations, only two significant figures would be used, and all samples were .1 gram or more in weight. Hence, a .001 difference would not be big enough to impact the SG value of that segment, and the samples would be considered dry and ready to weigh.

In addition to the 78 core samples collected in 2024, we included the SG data of 72 core samples from another study (Zampieri et al., 2024) measured using a similar method. These core samples were collected from all the Florida study sites from May to August 2018. The methods used for sampling across a broad range of these samples were discussed in Zampieri and Pau (2022).

1.2.3. Statistical Analysis

Correlation analysis and the Random Forest model were used to select and rank statistically significant variables based on the magnitude of correlation coefficients and the importance value of included variables to answer the first question. With the selected variables, the regression tree model was employed to examine further the effect of these variables and their interactions on SG of longleaf pine (the second question). The profile of the best regression tree model (i.e., the pruned tree model) explicitly displays the relative importance of included variables and their interactions based on their locations in the tree profile. After removing multicollinearity within the selected variables, a multiple linear regression (MLR) and geographically weighted regression (GWR) were conducted to quantify the global and local spatial patterns of SG variations and the impact of important variables. As a localized regression model, GWR is useful in revealing the locality (spatial variations) of the effect of potential driving variables on SG. All statistical analyses were conducted using statistical software R-4.4.2

and through the R packages including *rpart*, *randomForest*, *spgwr*, and *stats* (R Core Team 2014).

1.3. Results

Figure 3 shows the top ten important variables (out of more than 100 environmental variables) identified by the RandomForest model based on their contribution to the node purity in partitioning the SG data. It is evident that longleaf pine's SG is influenced by temperature, precipitation, and soil texture. Most of these variables are weakly correlated with SG based on the Pearson's correlation coefficients ($r < 0.4$), indicating that other variables that were not included in this study may affect longleaf pine SG as well. The regression tree model (Figure 4) shows that the low (≤ 0.6, the nodes to the left) SG was primarily influenced by the interactions of temperature and precipitation, while moderate and high (> 0.6, the nodes to the right) SG was controlled by the interactions of temperature, precipitation, and soil conditions. Longleaf pine produces wood of high SG on sandy soils with low available water capacity.

Both multiple linear regression and geographically weighted regression (GWR) models showed that, except for monthly precipitation from June to December (June_Dec_latewood_growingseasonPrec_nicole), all other variables globally had a negative effect on longleaf pine's SG (Tables 1 and 2). However, GWR showed that the effect of these variables on SG may change spatially (Figure 5). These variables had more prediction power of the change in SG in some areas (e.g., Southern Alabama and southwest Georgia) than other areas (e.g., southern Florida), as shown by the change in the localized R^2. These changes reflected the complexity between environmental variables and SG.

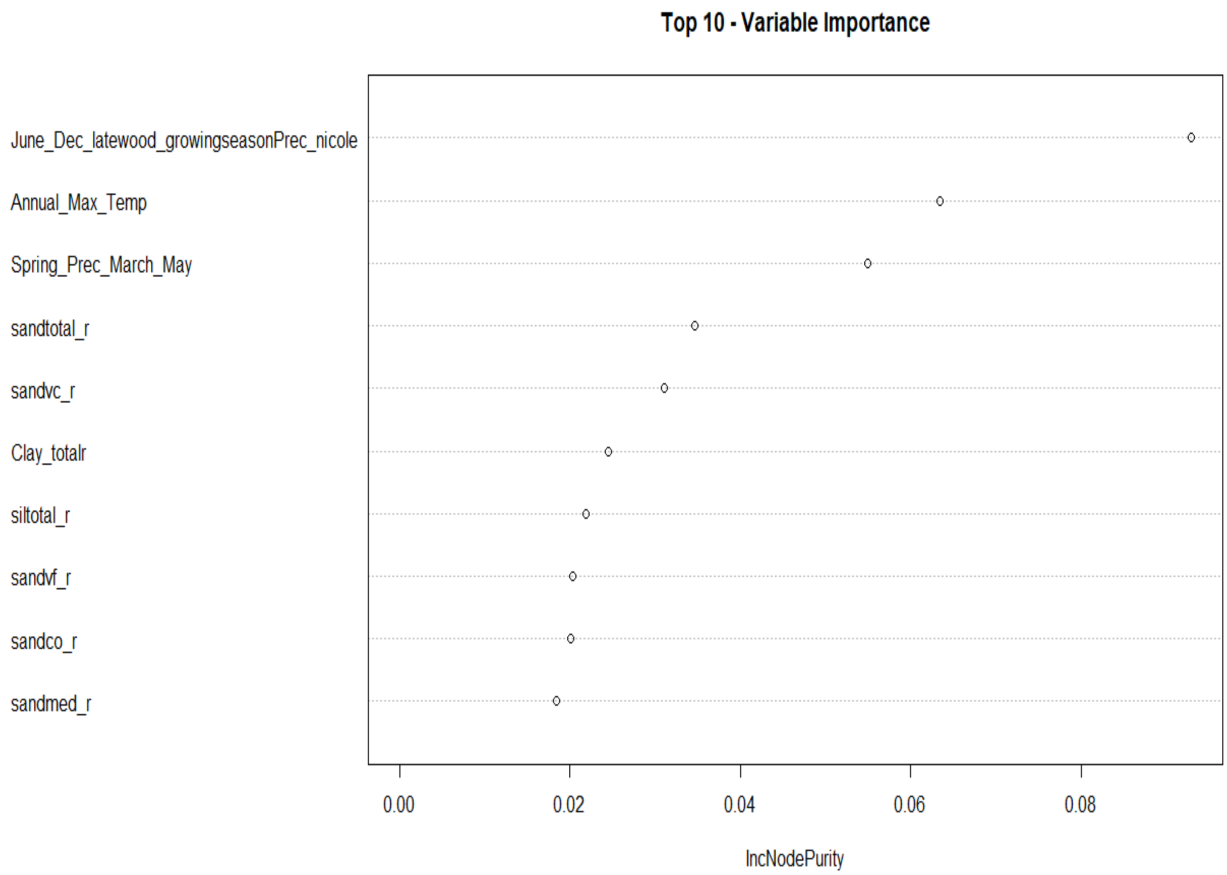


Figure 3.The relative importance of the top ten variables computed by the randomForest model.

The relative importance decreases from top to bottom, with the precipitation from June to December for latewood growth (June_Dec_latewood_growingseasonPrec_nicole), annual maximum temperature (Annual_Max_Temp), and March to May precipitation for earlywood growth (Spring_Prec_Mar_May) as the leading factors, followed by soil properties (sand and clay contents).

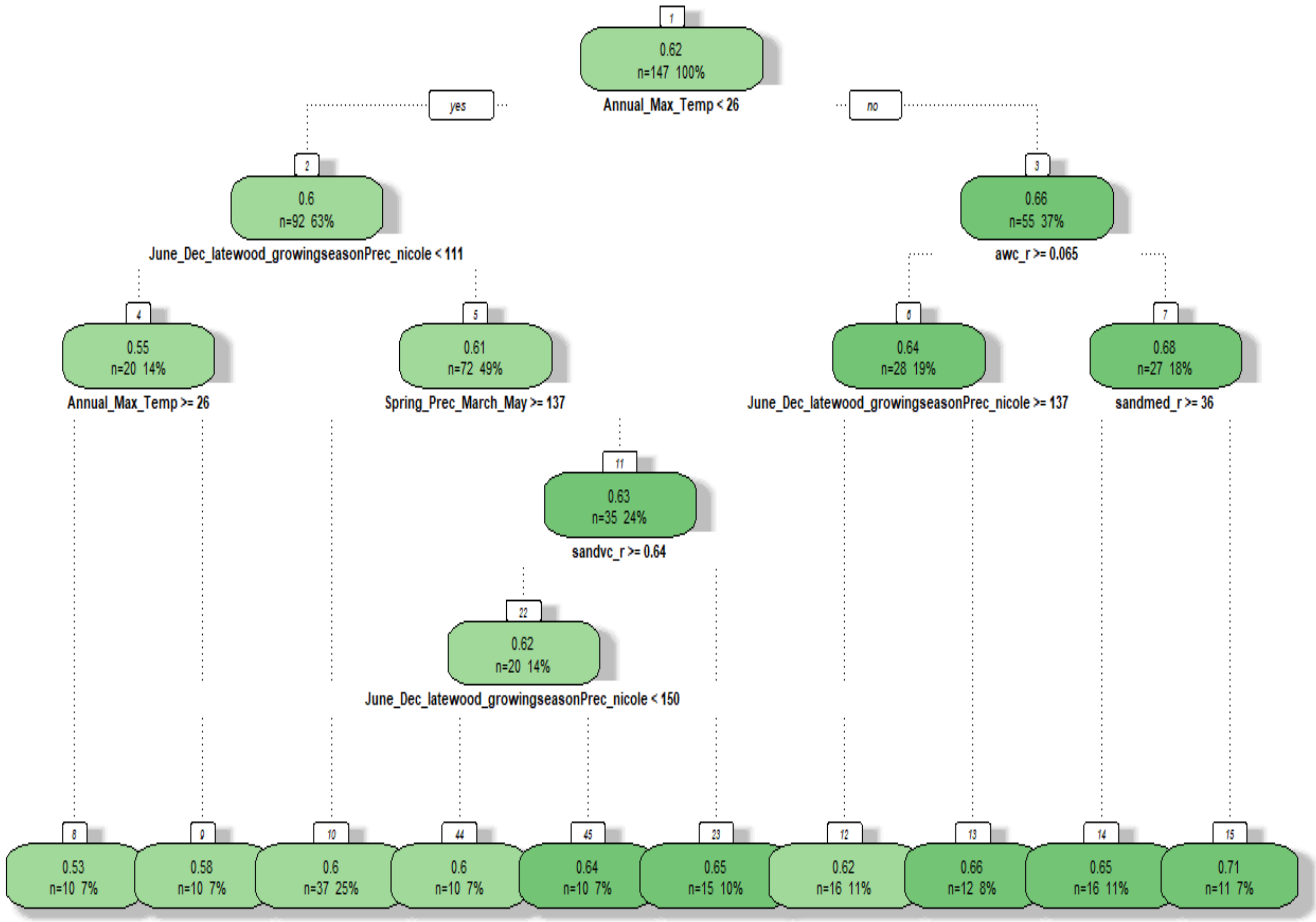


Figure 4. The best regression tree model of SG, showing the change in SG by selected variables and their interactions. The top number in each node shows the average SG value, and the two bottom numbers are the number and proportion of cores included in a subset

Table 1. Regression coefficients of the fitted multiple linear regression model of longleaf pine SG by selected variables*.

Variables	Estimate	Std error	t-value	p-value
Intercept	1.0916	0.2098	5.2020	<0.0001***
Annual_Max_Temp	-0.0159	0.0071	-2.2310	0.0275*
June_Dec_latewood_growing seasonPrec_nicole	0.0010	0.0003	2.8430	0.0052**
Spring_Prec_March_May	-0.0012	0.0005	-2.5410	0.0123*
sandvc_r	-0.0219	0.0045	-4.8800	<0.0001***
om_r	-0.0269	0.0110	-2.4520	0.0156*

*Adjusted $R^2 = 0.2816$; residual standard error = 0.0494; F = 11.1200; p-value < 0.0001

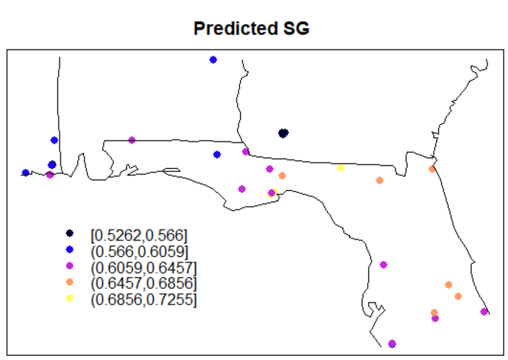
Table 2. Regression coefficients of the fitted geographically weighted regression of longleaf pine SG by selected variables*.

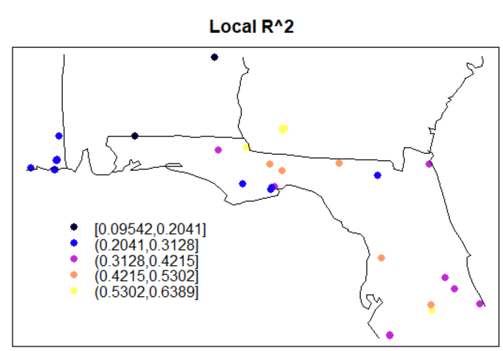
Variables	Regression coefficients					
	global	Min	1st Quartile	Median	3rd Quartile	Max
Intercept	1.1293	-10.6680	-0.0566	1.4056	2.4064	3.0596

Annual_Max_Temp	-0.0170	-0.0101	-0.0065	-0.0031	0.0040	0.0137
June_Dec_latewood_growing seasonPrec_nicole	0.0010	-0.0103	-0.0004	0.0003	0.0013	0.0448
Spring_Prec_March_May	-0.0014	-0.0067	-0.0033	-0.0020	-0.0008	0.0333
sandvc_r	-0.0189	-0.0532	-0.0247	-0.0120	-0.0030	2.2310
om_r	-0.0264	-0.0110	-0.0328	-0.0147	0.1772	1.1276

*Quasi-global R^2 = 0.5352; Residual sum of squares = 0.2213; AIC =-502.1005,

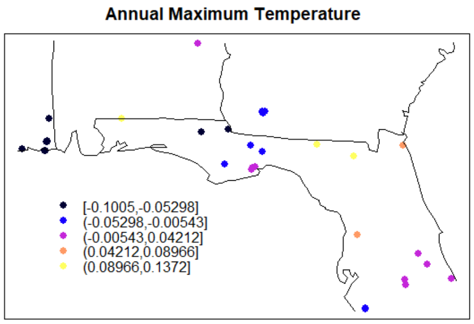
AICc = -438.2811

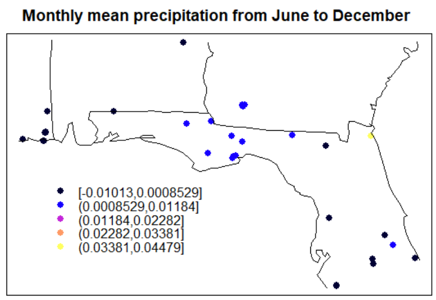




Fitted SG

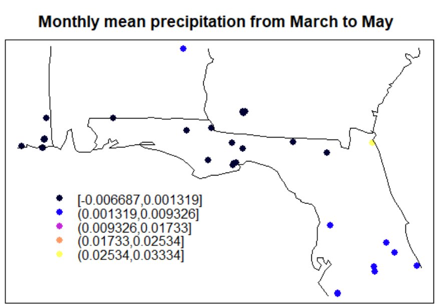
R-square

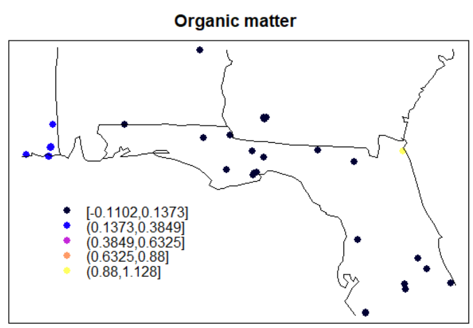




Annual Max Temp

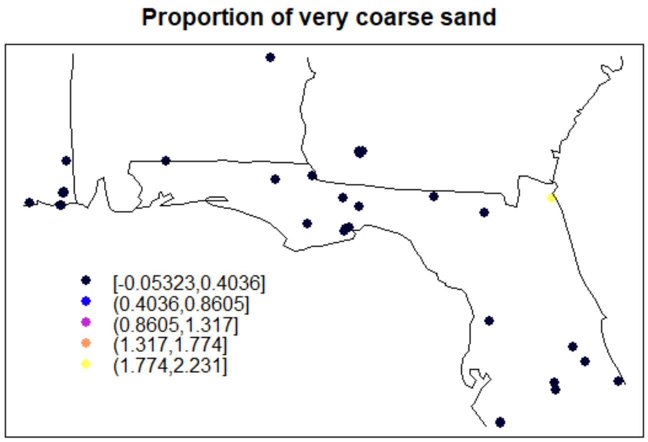
June though December Precipitation





Spring Precipitation

Organic Matter



Very Coarse Sand

Figure 5. The result of geographic weighted regression showing the regional change in SG, R-square, and regression coefficients for selected variables.

1.4. Discussion:

The effect of important variables and interactions on longleaf pine SG

Most of the interactions in Figure 4 result from the available moisture controlling the latewood and earlywood growth, causing the SG value to change. For the interactions that occur when the annual maximum temperature is under 26°C (node 1), the next node (node 2) is based on whether the precipitation for June through December (JTD) is above or below 111mm. If it is above 111mm, the SG will be higher than below (node 2). A possible explanation is that when the tree is above 111 mm, it has ample moisture during its latewood formation period. This ample moisture will cause productive latewood growth, which will cause the SG to increase as well (Rother et al., 2018; Zampieri et al., 2024).

Moving to node 4, the difference in maximum annual temperature, as an increase in temperature, especially during the late summer months, can decrease latewood growth, causing a decrease in SG (Zampieri et al. 2024). Because node 4 has less than 111 mm during its latewood growing season, the effects of a hotter temperature may be more impactful as moisture is limited by soil moisture evaporation and an increase in transpiration.

If the samples experienced a heavier latewood precipitation season (node 5), and the spring precipitation exceeds 137 mm, then the specific gravity (SG) will decrease. This is most likely because there is a positive correlation between earlywood growth and spring precipitation (Zampieri et al. 2024). Therefore, this increase in precipitation might have caused an increase in earlywood growth, which would make the SG lower as earlywood is less dense than latewood (Paul and Smith, 1963). Additionally, the SG values that have less than 137 mm of spring precipitation have more interactions (nodes 11 and 22). The first one (node 11) is that if the soil contains less than .64% of very coarse sand, it will have a higher SG value. This can be explained by the fact that very coarse sand may not be able to retain water due to its large pore size, causing limited water availability. Therefore, with the soil containing very small amounts of very coarse sand, the soil may retain water for longer, and therefore, there is more moisture available for the tree. Additionally, for these samples in particular, the precipitation is low in the Spring but high from June through December. Therefore, by the soil providing better moisture retention, it will cause the SG to increase rather than decrease because precipitation during the latewood season is favored over the earlywood.

Within the samples that contain more than .64% of very coarse sand, there is another interaction (node 22). For samples with more than 150 mm of average precipitation from June through December, the SG will be higher than for samples with less than 150 mm. This is also supported by the same evidence that explained node 2, which is that increased precipitation in June through December causes an increase in SG. Yet, it is crucial to consider that 150mm of precipitation is a lot for an average during the June through December months. Therefore, the increase in very coarse sand may help with drainage, preventing the pine from being flooded or oversaturated, which may cause growth suppression. This is a very important point because for samples that had an annual max temperature of 26, had available water capacity over .065 cm/cm, and had June through December precipitation higher than 137 mm, had a lower SG than samples with June through December precipitation lower than 137 mm (node 6). Node 6 had the opposite result of the same interaction as node 22. A possible explanation for this interaction is that the increase in available water capacity may indicate that the soil is not draining enough to accommodate the extreme precipitation during these months, causing oversaturation. This oversaturation or extreme precipitation might be causing growth suppression during latewood formation, producing a lower SG. Unfortunately, no literature was found to support this explanation, but it does explain why the latewood growing season precipitation has an opposite effect for the two interactions.

Unfortunately, we do not have an explanation for node 3. This is because it would be expected for the higher SG values to be where the higher available water capacity soil is, but the opposite is true for node 3. Additionally, node 7 does not have an explanation as well because of the available water capacity and the amount of medium sand in the soil. We are surprised by this result, as the two shouldn't interact with each other as they are both closely related.

Regional variations of regression coefficients from the GWR model

Spring precipitation

From the global GWR coefficient, SG and spring precipitation have a negative relationship. Our explanation for this relationship is that the higher precipitation in these months leads to more earlywood growth. More earlywood growth led to a lower overall SG as earlywood is less dense than latewood (Paul and Smith, 1963). This is supported by the literature as earlywood width was highly correlated with spring precipitation (March and April) (Henderson and Grissino-Mayer, 2009). Additionally, the earlywood formation months were found to be March through April for Florida and Southern Georgia (Rother et al. 2018).

Yet, when looking at the local coefficient of the geographic weighted regression, it seems that the northern points have a negative relationship with spring precipitation and the southern points have a positive relationship. This does not include the two sites that do not fit this trend. As seen in Figure 4, spring precipitation interactions occur when the annual maximum temperature is less than 26°C. Therefore, this difference in correlation type between the south and the north may be due to the difference in temperature. Therefore, since the spring precipitation interaction primarily affects colder regions, areas with warmer spring temperatures may see little to no impact. As a result, the higher spring precipitation observed in the southern study area may be associated with increased latewood precipitation or overall precipitation. However, precipitation outside of the spring months only affects latewood production. Since spring precipitation does not impact warmer areas, it mainly reflects latewood precipitation, which has a positive relationship with SG. This can be a possible explanation for the coefficients of the GWR. Yet, we are not sure why this phenomenon is occurring, as it does not align with our previous ideas of how spring precipitation would impact SG. Additionally, the global GWR coefficient was the weakest out of all the correlations. This makes sense as many dendrochronology studies have found that earlywood is not as sensitive to climate as latewood

(Zampieri et al. 2024, Soulé et al 2021). One study even stated that the widths of earlywood do not vary as much as latewood (Harley et al., 2023). With precipitation during these months only impacting earlywood production, it makes sense that it would impact SG, but as much as the other variables, which SG changes based on latewood production.

Content of very coarse sand

The global relationship found that very coarse sand and SG have a negative relationship. As mentioned before, the amount of precipitation impacts both earlywood and latewood growth (Soulé et al., 2021; Henderson et al., 2009; Henderson and Grissino-Mayer, 2009). Essentially, precipitation provides the tree with moisture. Yet, other factors, such as soil, can influence the amount of moisture available to trees.

The very coarse sand is defined as “Mineral particles 1.0mm to 2.0mm in equivalent diameter as a weight percentage of the less than 2 mm fraction” (Soil Survey Staff). This is considered the largest soil particle from the standard soil textures (clay, silt, and sand). With coarser soil textures, there is a lack of available water capacity since the large pores created by this soil texture allow for more free drainage (USDA Natural Resources Conservation, 2008). With more sand, it means more drainage, which means less soil moisture retention, and therefore less variable moisture to the tree. Consequently, we believe this reduction in soil moisture is causing growth suppression only to the latewood ring. We think it is only the latewood ring as it has been found that earlywood width is not impacted by climate nearly as much as latewood (Zampieri et al. 2024, Soulé et al 2021). Therefore, even though both seasonwoods are subjected to decreased moisture, latewood will be affected more. For the GWR coefficients, it seems all the study sites except for three have the same negative correlation. Additionally, with the three sites that do have a positive correlation, we are not sure why this is occurring. More research will need to be done to investigate why these three sites are positive.

Annual maximum temperature

The global regression shows that as temperature increases, SG decreases. Additionally, it has been found in the literature that latewood growth has been negatively correlated with late-season maximum temperature (Zampieri et al., 2024). Therefore, the negative relationship between SG and temperature is most likely due to high temperatures causing growth suppression for latewood. The exact reason why temperature impacts latewood growth is unclear, but it may have to do with the increase in evapotranspiration stress and a possible lack of available moisture, which may inhibit growth (Zampieri et al., 2024; Way and Oren, 2010). However, when examining the local coefficients (Figure 5), there is noticeable spatial variability, although the underlying causes remain unclear. The southern region would be expected to exhibit a negative relationship with maximum temperature, given the more extreme temperatures in that area, which could amplify the harmful effects. However, the opposite was observed, with the southern region displaying a positive relationship. More research is needed to explore this spatial distribution and its causes. Yet, it was also found that the south part of the longleaf pine range is less sensitive to climate than the northern region, which may help explain why the southern sites exhibited weaker correlations than those in the north.

Organic matter

The results show that the higher the percentage of organic matter in the soil, the lower the SG would be. According to Zobel and Buijtenen (1988), the use of fertilizer decreases the specific gravity because it increases the earlywood production but has little to no effect on latewood production. Therefore, the organic matter in the soil most likely has some of the same valuable nutrients that fertilizers have, causing a similar effect. This phenomenon has been seen in Loblolly, where fertilizer application caused a lower ring SG value (Antony et al., 2009). It was also found that longleaf pine grown on cutover sites had a higher SG than longleaf pine grown on agricultural fields. The cause of the difference in SG between the two sites was that the agricultural fields had residual fertilizer that supplied more nutrients than the cutover site (Raut et al., 2022).

Additionally, the organic material in a soil increases the soil's ability to hold water (USDA Natural Resource Conservation Services). Therefore, having water available for longer may help earlywood production, along with the nutrients, causing a lower SG. For the local coefficients, most of the spatial distribution had negative correlations, which agrees with our explanation. Yet, there are a couple of sites that have a positive relationship with SG. There seems to be one site with an extremely high correlation compared to others. Further investigation of this specific area is needed to see if the high correlation of that study site is due to its location or if it is an outlier in the data. More research needs to be done to explore why fertilizer only affects earlywood growth but not latewood growth, and why both positive and negative relationships occur, as the literature has only found negative relationships with SG.

June through December precipitation

The results show that as the precipitation during the months of June to December increases, so does the SG. This phenomenon has been seen in two other studies with slightly different species. For the southern pines (including Longleaf Pine), it was found that Florida Southern Pines have a higher SG due to the heavy rains during the late summer. Another study, for Loblolly, found that when the species was grown in California (an area with very limited late summer precipitation), it had a much lower SG than usual. This was because the California climate was characterized by early spring precipitation and had little to no rain in the late summer months, causing the rings to be earlywood with little to no latewood (Zobel Buijtenen, 1989). This evidence is also supported by Soulé et al. (2021), as they found that adjusted latewood growth had a very strong relationship with rainfall during the months of July through September. In Rother et al. (2018), they found that for Southern Georgia and Florida, latewood formation occurs from July to December for all sites, with June being the transition period between earlywood and latewood.

What we think most likely occurred is that ample precipitation from June to December not only allows latewood to grow through the entire season but also increases the amount of growth produced. The more latewood produced, the higher the SG will be. For the local coefficients, most of the study sites aligned with our global coefficient, except for a couple. We are not sure why some areas have a negative relationship, as there does not seem to be a clear pattern. Further research and additional samples in the neighboring regions are needed to confirm that the negative relationship is true or an artifact.

Data quality

We should acknowledge that the SG data for this chapter comes from different data sources. The Florida SG dataset was kindly provided by Dr. Nicole Zampieri. Her methodology was similar enough to our methods, but it had some differences that should be addressed for transparency. First, Dr. Zampieri used 5mm cores instead of 12mm cores and did not segment the cores. The volume estimation was done immediately after the core was taken from the tree, instead of being frozen. The volume estimation method was done by water displacement, as described in Williamson and Wiemann, (2010), which is comparable to our volume estimation method using calipers. In her analysis, she retained the bark on the samples, unlike our approach, where we removed it. While the presence of bark may introduce some variability, it is unlikely to compromise the overall comparability of the dataset to ours. Her samples were not cross-dated, and the extractives were not removed. She also followed the same methodology we used to dry the samples in the oven.

The Escambia dataset was processed with the same methodology as the other datasets (besides Florida) but with a slight difference. Because this dataset was originally created and used for another study of longleaf pine resilience following droughts, the segmenting of the cores is based on certain drought years. Therefore, the core is segmented and has been calculated using the weighted average technique, but the segmentation is not every 5 years or in intervals of 5.

In summary, because SG can be used to estimate biomass, which is then used to estimate carbon storage, SG can be a loose indicator of carbon sequestration. Understanding the spatial pattern of SG and what is causing it can impact where carbon markets decide to start Longleaf Pine plantations. Most importantly, understanding the spatial pattern of SG can lead to more accurate models for biomass and carbon, and carbon markets can make more accurate assessments because they know where the carbon is stored within species.

1.5. Conclusion:

We found that environmental variables significantly influence SG in Longleaf Pine. Specifically, SG was negatively correlated with maximum temperature, spring precipitation, and sand content. In contrast, SG positively correlated with precipitation from June through December. These findings may be explained by the influence of environmental variables on earlywood and latewood growth, which in turn affect SG. However, further research is needed to confirm that these factors are the primary drivers of SG variation. Additionally, we found within each variable that the local correlations with SG varied, some even being opposite to the global relationship. More research is needed to investigate the cause of this variation in spatial distribution. These results are crucial, highlighting the need for SG values that go beyond species-specific data to obtain accurate biomass estimates. Finally, these results are highly valuable, as they can inform decision-making regarding the optimal locations for Longleaf Pine plantations in carbon markets.

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Chapter 2

Temporal Variations of SG in Longleaf Pine and Driving Factors

2.0 Abstract

Accurate tree carbon storage estimates are essential for an effective carbon market. Wood specific gravity (SG), as a carbon indicator, provides a more accessible tool for understanding carbon than traditional destructive sampling, as the SG value can be directly used to estimate tree stem biomass through volume conversion. However, anthropogenic climate change altering weather patterns may drastically impact carbon storage because carbon storage heavily relies on available moisture. For longleaf pine, past the ring count of 62, there is very little information on how carbon is stored in high ring count (age) trees. Therefore, it is essential to understand how ring count, climate, and interactions affect carbon storage from a temporal perspective. In this study, we attempt to understand how different climate variables (PDSI, precipitation, temperature, and vapor pressure deficit) and soil (available water capacity, sand, silt, clay, and organic matter) impact wood specific gravity (SG). Our main finding was a strong negative relationship between SG and ring count after the year 62. Additionally, we also found that both precipitation and very coarse particles (sand) had a positive relationship with SG.

Keywords: radial pattern; specific gravity; carbon;

2.1. Introduction:

Longleaf pine (*Pinus palustris*) is an important conservation species in the southeastern United States with significant potential for carbon storage. Its high specific gravity enables it to store more carbon while alive and for a longer period after death (Kush et al. 2004). Longleaf pine can grow in various habitats and is tolerant to fire and many diseases, living longer than other pine species (Johnsen et al. 2009, Churchhill et al. 2013). This makes it potentially better able to adapt to climate change than other tree species for carbon sequestration (Samuelson et al. 2016).

Many studies have noted radial variation in SG or the impact of cambial age (age from the pith) on SG (Zobel et al., 1972; Eberhardt and Samuelson, 2015; Eberhardt et al., 2018). Age from the pith is critical in relation to SG, since SG tends to rapidly increase with the ring count from the pith, followed by a slow increase or even slight decrease thereafter to a certain cambial age (Zobel et al., 1972). Longleaf pine has been reported to have a type-1 radial variation- as the cambial age increases, so does the specific gravity (Schimleck et al., 2022). Yet, examination of published data shows slight or moderate differences occur after the cambial age of 40 (Schimleck et al., 2022). A slight decrease in SG after the ring count of 40 is observed (Eberhardt and Samuelson, 2015; Eberhardt et al., 2018) and continues until the end. The issue is that the radial SG pattern reported only goes up to a ring count of 65, which is considered small, as Longleaf Pine can live up to 400 years (Frost, 2006). To our knowledge, there is little to no literature on mapping the radial pattern of SG beyond 65 ring counts. However, this information is critical to quantify the ecosystem's carbon sequestration rate and map the carbon stock across the chronosequence or different developmental stages of forests (Sameulson et al., 2016).

The radial pattern in SG is related mainly to the relative proportion of earlywood and latewood within a ring, subject to genetic and environmental factors (Lachenbruch et al., 2011). Differences in SG of different species grown under approximately the same environment have been found, but the underlying causes and implications were poorly understood (Fortunel et al., 2014; Bastin et al., 2015). For instance, when growing on the same site, longleaf pine almost always produces wood of higher SG than slash and loblolly pines. The wood development pattern between these tree species was different, and part of it was caused by juvenile wood production (Zobel et al., 1972). The length of the period of juvenile wood production may significantly affect the radial pattern in SG, especially when the increase in SG stops at a certain age (ring count) and the increasing trend in SG starts to change into a decreasing trend.

Our understanding of how environmental variation influences radial SG patterns across a species' geographic range is minimal. This variation in wood density among species can affect estimates of woody biomass and its role in carbon cycling. Understanding how climate impacts SG from year to year is incredibly important, as the current climate is changing, with increasingly severe weather, such as droughts, that may affect the SG of Longleaf pine. One dendrochronology study looking at the relationship between climate-growth for Longleaf showed that post 1950, the direction and correlations of the relationships between growth and climate variables shifted (Zampieri et al., 2024). This shows that the current climate change is affecting Longleaf Pine growth, which will most likely impact SG. Therefore, it is critical to understand how SG reacts to climate from a year-to-year perspective, as it is and will most likely continue to change.

In this study, we plan to map out the radial pattern beyond 65 ring count to better understand how older or high-ring-count trees store carbon in Longleaf Pine. If ring count significantly impacts SG, it will be essential to include its effects when testing SG against other variables. Specifically, we are attempting to understand what factors cause the variation between SG rings. Three main factors that impact the temporal SG: ring count, climate, and soil, will be included. The climate variables will remain the same as in the first chapter. This is because the climate variables change year to year and may explain the difference in SG from year to year, based on the literature in the first chapter. In addition to those climatic variables listed in chapter 1, another climate variable, the Palmer Drought Severity Index (PDSI), will also be included. By measuring moisture availability, this variable can tell if a year is wetter or drier than normal and may be a valuable metric to test how differences from normal moisture conditions could impact SG from year to year.

The soil could change even though the longleaf pine samples collected for this study grew under the same climatic conditions. Hence, soil properties (texture) directly related to water availability were included, as the difference may impact SG and better explain the variations in its radial pattern. Specifically, we aim to answer two fundamental questions: 1) What kind of radial pattern does longleaf pine SG take, especially beyond the ring count of 65? 2) How much do the climatic and soil variables explain the longleaf pine radial SG variation? Answers to these questions will help us better understand the temporal patterns of carbon sequestration and stock in forest ecosystems.

2.2 Methods

2.2.1 Study Sites:

All core samples to measure longleaf pine SG were taken from the Jones Center, a private conservation research center in Ichauway in Baker County, Georgia, USA (Figure 6). Located in the subtropical climate zone, its annual precipitation ranges from 762 mm to 2004 mm, averaging 1310 mm. The annual average temperature ranged from 17.9°C to 21.2 °C with an average of 19.5 °C. The annual minimum temperature ranged from 11.2 °C to 14.7 °C with an average of 13.0°C. The annual maximum temperature ranged from 24.2 °C to 28.5 °C, averaging of 26.0°C. The yearly minimum vapor pressure deficit ranged from .17 hPa to 1.31 hPa with an average of .74 hPa. The annual minimum vapor pressure deficit ranged from 15.38 hPa to 24.08 hPa, averaging 18.87 hPa (The PRISM Climate Group, 2025).

The study sites range in different soil types. The soil ranges from 12.91% to 21.31% for the total amount of clay with an average of 15.1%. The soil ranges from 8.67% to 12.61% for the total amount of silt, with an average of 11.35%. The soil ranges from 66.15% to 77.58% for the total amount of sand, with an average of 73.58 %. The soil ranges from 0.21% to 0.73% for the total amount of organic matter, with an average of 0.39%. Additionally, all the soil had a 0.11 cm/cm for available water capacity (Soil Survey Staff).

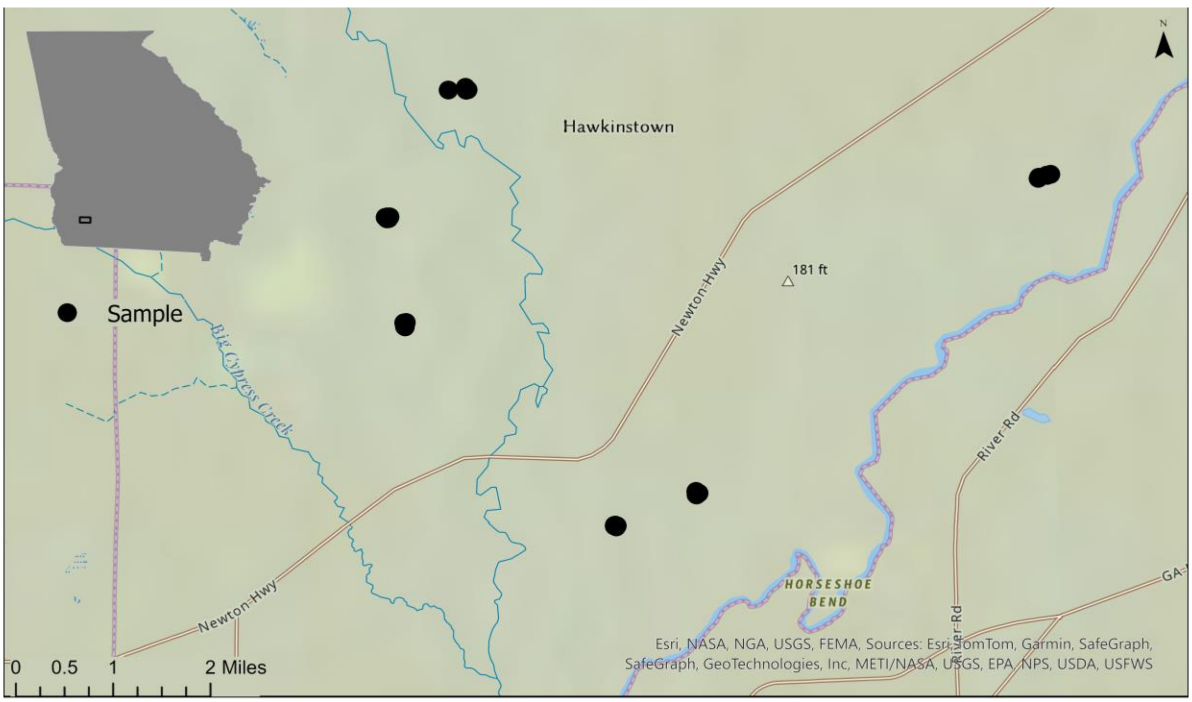

Figure 6.Map of field sampling points of longleaf pine specific gravity in the Jone Center at Ichauway, Georgia

2.2.2. Field sampling, core segment processing, and measurement

Thirty-seven healthy longleaf pine trees of different sizes (ages) from six sites (stands) were identified in the Jones Center (Table 3). One core sample was taken at breast height (4.5 feet) from each tree using a 12 mm increment borer on August 7-8, 2024. Cores were placed in a zipped plastic bag within a cooler with ice during transportation and stored in a freezer before processing to ensure they remained at or above the fiber saturation point (30% moisture content (MC)) for accurate green volume measurements (Forest Products Laboratory, 1987). Cores were then cut into 5-ring segments using an Xacto knife before volume and weight measurements to calculate SG. After removing flawed core samples and/or segments, 525 segments were generated from 30 cores in all study sites, dating back to 1888 to 2023 (Table 3). Core segments were cross-dated for a serial trend analysis, and resin was extracted using Acetone for an accurate estimate of SG according to Via et al. (2004). Core segment volume and weight measurements follow the same procedures described in Chapter 1, in accordance with Williamson and Wiemann (2010), except for some minor modifications described as follows.

Table 3. Longleaf pine tree cores sampled in the Jones Center at Ichauway, Georgia

Core sample No.	Ring Count	DBH	Number of Segments	Number of Segments Used
1	95	24	18	17
2	135	22	24	20
3	60	13.5	12	11
4	76	NA	16	15
5	57	22	12	11

6	94	13.5	20	20
7	111	NA	20	19
8	113	NA	21	19
9	61	22.1	13	13
11	56	14.5	11	8
12	68	15.5	14	12
13	88	20.5	16	13
14	100	NA	20	19
15	71	16.2	13	10
16	42	18.5	9	10
17	40	14.1	8	7
18	57	11.5	12	9
19	99	18.5	18	13
20	99	21	20	18
21	73	17.5	15	13
22	83	20	16	15
24	79	22	17	14
26	53	17.2	10	8
27	58	16.3	12	10
28	55	12.7	11	10
29	57	13.5	12	10
30	53	23.1	10	8

31	62	25.5	14	14
32	82	16.5	16	13
33	75	NA	14	12
34	73	17	15	13
35	94	17.7	19	18
36	28	NA	6	6
37	84	NA	18	18

Cross dating of core segments

Once the core sample was dry, it was mounted using Elmer's Glue and sanded using 80 grit to 600 grit sandpaper. The samples were scanned at 1200 dpi resolution using an Epson Perfection v600 flatbed scanner. The samples were visually cross-dated in Coorecorder and statistically cross-dated using Cdendro. The mean interseries correlation was .51, which is in range compared to similar studies with Longleaf Pine (Soulé et al., 2021 and Zampieri et al., 2024).

Segmenting core samples

The core segments were cut into intervals of 5's with some being bigger (but still a factor of 5), like the first chapter. The difference is that any segment with a ring count larger than 5 was not included because the SG value would be too generalized and not comparable to the 5-year intervals. Yet, because we wanted the calendar years also to be increments of 5 (ex., 1950 to

1955), some pieces were less than 5 years but were still included since they would only be more accurate. Also, because the last calendar year for the cores was 2023, if we did not include pieces less than 5 years into the dataset, we would eliminate almost all core end and beginning pieces. This would limit our ability to test variables like sample distance for pith, which are critical for this study.

Extracting resin with Acetone

Tree resin might be an important factor that affects the accuracy of calculating the core segment's SG. For tree resin specifically, it may inflate the SG value by adding weight to the wood. This was seen in Via et al. (2004), where 10 wood discs from different longleaf pines sampled at breast height were extracted through resin. The weight of extractive materials may take up 2.6 to 30.5% of the total wood weight (Via et al., 2004). The removal of tree resin will be done through acetone extraction following the procedure outlined in Eberhardt et al., (2018), Eberhardt, (2019) and So et al., (2018) with some changes. Core samples were soaked in acetone for two weeks, changing the acetone every two to three days. A rotary evaporator was used to recycle the acetone to determine when the extraction was completed since no solids (tree resin) should be left after the acetone evaporation. Because we did not have access to a rotary evaporator, we decided to use the weight before and after an acetone cycle as the indicator to determine if extraction was completed. Four samples that were visibly considered the most resin saturated out of all the samples were chosen to be the test samples. These test samples were weighed before and after soaking in acetone for at least two days (this is considered one acetone cycle) to see if the weight had decreased or stayed constant. If the weight had decreased, the sample still had tree resin that needed to be extracted, and another cycle would be needed. If the weight had stayed the same, the extraction would be considered completed.

The samples were soaked in acetone at room temperature for a total of 32 days and a total of 4 acetone changes. Due to different factors impacting the weight of the sample, additional procedures were put in place to make the before and after test weights comparable. The first additional step was ensuring the acetone completely evaporated out of the test sample. This was accomplished by wiping off the excess acetone from the test samples and then letting them dry in the fume hood. After a few hours, the test samples were put on a .0000 precision scale, and if the weight was decreasing, acetone evaporation was still occurring. If this happened, the samples were either put back into the fume hood for another hour or in an oven at 90 ^{o}C for 20 minutes and weighed again afterward. This process was repeated until the weight was constant or increasing. The weight increase on the scale was considered because it indicates moisture absorption from the air. The second step was after the acetone evaporation, where the samples were put in a humidity- and temperature-controlled room (relative humidity = 49.5% and temperature = 12.8 °C) for 15 hours. This was done so that the sample's moisture content was similar enough that the weights would be comparable. Even with these accommodations, external factors may influence the weights at such a delicate and precise scale. Therefore, only the two significant decimal points of the weights were used to determine whether the sample reached a constant weight.

Green volume estimation:

Because the samples were air dried, we had to rehydrate them to reach the fiber saturation point. To accomplish this, we first took the weight of each dry segment. Next, the segment was placed in water with a weight to ensure it was completely saturated in the water. The next day, the excess water would be removed from the segment with a paper towel, and the weight would be taken. The dry and saturated weights would be used to calculate the moisture content (MC) (found in section 1.2.2). If the MC was at or above 30%, it was considered above the fiber saturation point and therefore was considered green volume (Forest Products Laboratory, 1987). After the segment was confirmed to be over 30% MC, the volume measurements were taken immediately.

Since the surface of the core was sanded for cross dating, a new volume estimation formula would have to be used. The volume of a partially filled cylinder (Figure 7) can be calculated using equation (1)

$$PFC = L\left(R^2 \cos^{-1}\left(\frac{R-D}{R}\right) - (R-D)\sqrt{2RD - D^2}\right) \qquad (1)$$

where the PFC stands for the volume of the partially filled cylinder, L is for length, R is for radius, and D is for depth.

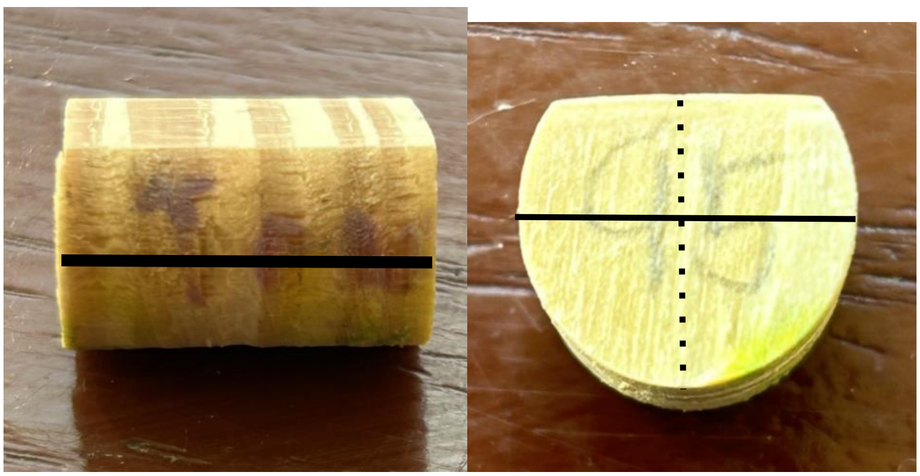

Figure 7. Image of the partially filled cylinder of tree core segments. The solid line on the left image shows how the length will be measured for the partially filled and regular cylinders. The solid line on the right image shows how the diameter will be measured for partially filled cylinder.

Oven-dried weight and SG calculation of core segments

After the volume of the samples was taken, they were left out to air dry in a fume hood until completely dry for weight measurements. The information can be found in section 1.2.2 labeled "Measuring Green Weight and Dry Weight".

A core segment's SG was calculated as,

$$SG = \frac{Ovendried\ weight(g)/Green\ volume\ (mm^3)}{0.001\ (g\ mm^3)} \qquad (2)$$

2.2.3. Environmental and ring count variables

In addition to the Palmer Drought Index (PDSI), the same set of climate and soil data as those in Chapter One was used in Chapter Two. For ring count, because the segments contained five rings, traditional ring count could not be used in this study. However, a comparable variable was created as a substitute. This variable was named maximum distance from pith. Essentially, this variable would contain how far the oldest ring of a sample was from the pith in units of rings. For example, if the oldest ring on the sample was 1950 and the year of the pith was 1900, then the oldest ring of the sample would be 50 rings away from the pith.

The annual and monthly Palmer Drought Severity Index (PDSI) data from 1895 to 2024 were collected from the National Centers for Environmental Information (https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/county/mapping) at the county level. The reason to include the PDSI in the data analysis of this chapter is that the PDSI is considered a temporal variable since it compares the selected year to previous years to see if the year was drier or wetter, which may better correspond to the serial trend of the core segment’s SG.

2.2.3. Statistical analysis

The smoothing spline regression model was conducted using the *ss* function in the R: *npreg* package to fit the radial pattern of longleaf pine SG (Question 1). The smoothing parameter was selected through the generalized cross-validation (GCV) method. Given an appropriate smoothing parameter, the smoothing spline will accurately quantify the radial pattern of longleaf pine SG that the parametric model cannot, including the increasing, decreasing, and leveling SG trend, and potential inflection points corresponding to the ring count embedded in the longleaf pine SG data.

Correlation analysis and the Random Forest model were used to select and rank statistically significant variables from a large candidate pool of 130+ climatic and soil variables. After repeated selections, only those variable sets without multicollinearity were kept for regression analysis. Considering the temporal (serial or auto-) correlation among the core segments, SG data were first detrended before running the generalized linear model using the selected variable sets as the predictors to evaluate their effect on SG (Question 2).

All statistical analyses were conducted using statistical software R-4.4.2 and through the R packages including *npreg*, *randomForest*, *TSA*, and *stats* (R Core Team 2014).

2.3. Results

The smoothing spline of longleaf pine SG shows an evident increase (ring counts: 1-20), leveling off (ring counts: 20-40), and a decreasing trend (ring counts > 40) (Figure 8). The SG of longleaf pine core segments ranges from 0.35 to 0.70, averaging 0.53 (95% CI: 0.520-0.532).

Greater variations in SG occur in the ring counts of 1-20 and > 40, suggesting that more variables might be involved in the juvenile and late-season wood production periods.

Among selected variable sets, PDSI and the proportion of very coarse sand have proved to be the best for quantifying the radial variations in SG, even though the models only explain approximately 9% of the variations in SG. Both variables positively correlate with SG, suggesting the potential impact of moisture availability on SG. The minor changes in the regression coefficients of PDSI under different periods of latewood growth indicate that moisture availability and its regimes (i.e., its distribution across months and seasons) may also affect longleaf pine SG values.

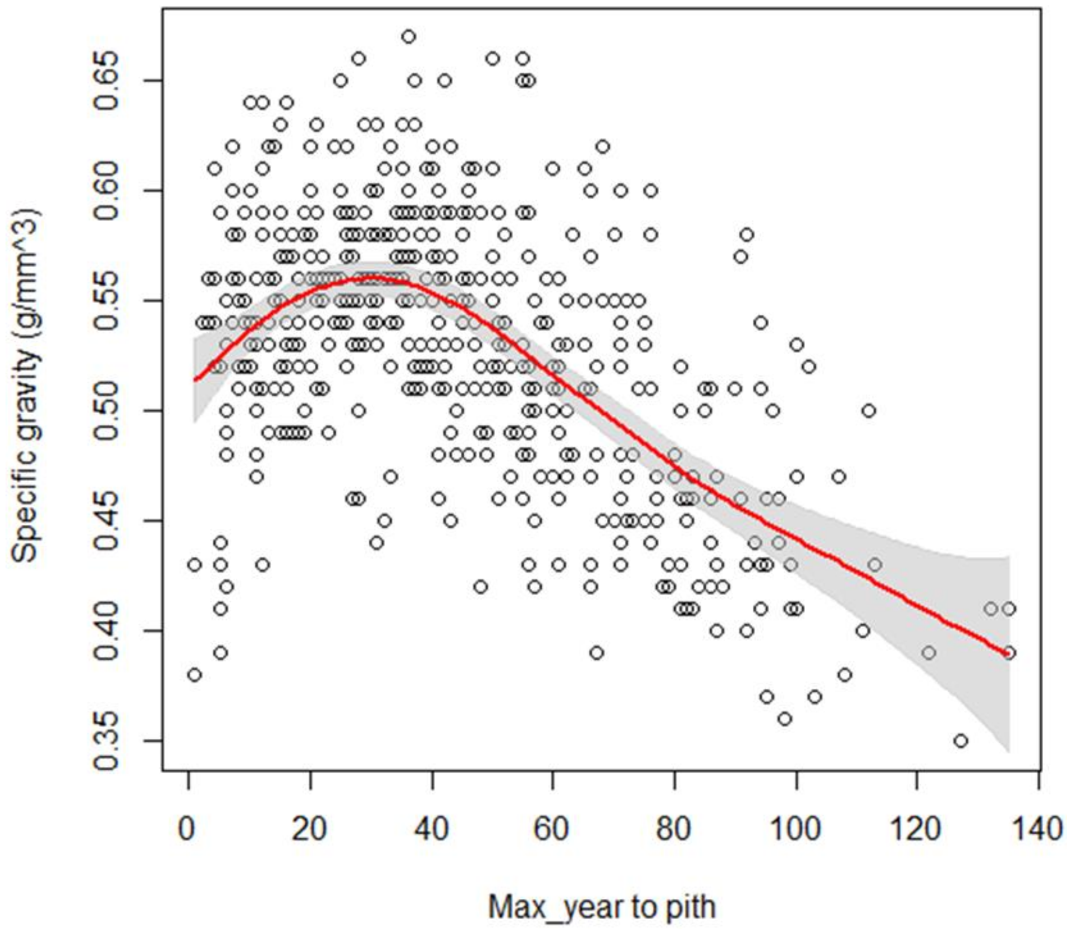

Figure 8. The splined serial trend of specific gravity of longleaf pine in the Jones Center at Ichauway. The shaded area shows the 95% confidence interval.

Table 4. Estimated regression coefficients of the detrended multiple linear regression models (A through D).

A)

Variables	Estimate	Std. err	t-value	p-value
Intercept	-0.0468	0.0095	-4.94	<0.0001
Annual PDSI	0.0131	0.0032	4.08	<0.0001
Very Coarse Sand	0.0167	0.0031	5.36	<0.0001

- Adjusted $R^2 = 0.0934$

B)

Variables	Estimate	Std. err	t-value	p-value
Intercept	-0.0472	0.0094	-4.99	<0.0001
PDSI Average from June	0.0127	0.0029	4.41	<0.0001

through December				
Very Coarse Sand	0.0168	0.0031	5.41	<0.0001

- Adjusted $R^2 = 0.0949$

C)

Variables	Estimate	Std. err	t-value	p-value
Intercept	-0.0474	0.0094	-5.02	<0.0001
PDSI Average from June through January of the following year	0.0136	0.0031	4.42	<0.0001
Very Coarse Sand	0.0167	0.0031	5.38	<0.0001

- Adjusted $R^2 = 0.0950$

D)

Variables	Estimate	Std. err	t-value	p-value
Intercept	-0.0480	0.0094	-5.09	<0.0001
PDSI Average from June through February of the following year	0.0139	0.0032	4.33	<0.0001
Very Coarse Sand	0.0169	0.0031	5.44	<0.0001

- Adjusted $R^2 = 0.0946$

2.4. Discussion

The radial trend of longleaf pine SG

A similar radial trend (increasing-leveling off-decreasing) of longleaf pine SG was found in this study, as reported by Eberhardt and Samuelson (2015) and Eberhardt et al. (2018). This relationship is also seen in Slash Pine (*Pinus taeda*) (Schimleck et al., 2022; Zobel and Buijtenen, 1989). The SG increases rapidly in the beginning years, which is considered the time of juvenile wood, and then levels off, which is the beginning of when mature wood is formed (Zobel and Buijtenen, 1989). However, this study's timing from the juvenile wood to transition to mature wood differs slightly from previously mapped radial variation patterns (Eberhardt et al.,2018; Sandera, 2022). Factors such as site condition and forest management may contribute to this difference. Sandera (2022) found that cutover sites transitioned from juvenile wood to mature wood earlier than in old agricultural fields. Additionally, improved forest management, such as fertilization, may increase the percentage of juvenile wood per ring (Zobel and Buijtenen, 1989). Yet, the question remains: Why does SG start to decrease around year 40? We believe that the latewood percentage decreases or the season wood becomes less dense as the ring count increases.

First, earlywood depositions are generally poorly understood. Some argued that earlywood is not controlled by climate as much as latewood (Zampieri et al. 2024, Soulé et al 2021), and earlywood growth is genetically controlled (Cosgrove, 2000). Because of the large size of the tracheids in earlywood, water transportation happens more through earlywood cells than latewood cells (Bjorlkland et al., 2017), and latewood is more important as it is the main source of water transportation for trees. Therefore, latewood is denser than earlywood and therefore stronger. The latewood may be essential when the tree has a low ring count and needs to have a strong enough core for high winds. But once it has developed its strong core, the need for latewood is not as essential as the functional need for earlywood. Therefore, over time, less latewood is produced, but the earlywood stays the same, which causes SG to decrease with ring count

For evidence of a decrease in latewood growth, Rother et al. (2018) found that larger diameter trees were more likely to go dormant during January and February than smaller trees. It is important to note that the dormant period is during the latewood growth season. In bigger trees, the latewood formation period ends earlier than in smaller trees, which may result in bigger trees having a lower SG than smaller trees. How does this relate to our study? The first conclusion would be that a bigger DBH indicates a high ring count and therefore high ring count trees are going through dormancy earlier than low ring count trees, which explains the difference in SG. While this relationship between DBH and ring count is logical, it is not always true, as tree ring growth rates have a significant influence on the DBH. This alone is not evidence enough, but another study on 80-year-old Slash Pine in the National Key Deer Refuge, FL, found that all their trees went through a dormant stage, with half of them beginning in December through January and the remaining being dormant for only January (Harley et al., 2012). If we assume that the DBH correlates with ring count for the Rother et al. (2018) findings, this dormancy period increase is the result of using high ring count trees for analysis. Yet, it is important to consider that the studies had different study site locations, and that the location might influence the dormant period. Yet, when comparing the Avon Park, FL (Rother et al., 2018) phenology with the Harley et al., 2012 phenology, the cambial phenology is almost identical, with the only difference being when the dormancy periods occur. Therefore, there is a possibility that the sites are not different in cambial phenology due to location, which makes cambial age the most influential factor. Unfortunately, this is just a possible explanation; other factors may be the cause instead of the ring count. Therefore, a direct study will be needed to evaluate if high ring count trees go through dormancy (or a more extended dormancy period) than low ring count trees.

This explanation above may explain why the SG is lower in high ring count trees overall, but it doesn’t explain the gradual decrease pattern. Our second explanation might shed light on why this is happening. It may be that as the tree increases in ring count, the lumens of the cells may be expanding, and the cell walls may become thinner. This might be a possible explanation, as it has been found that the cell wall thickness in latewood has a significant impact on the SG if the latewood percentage does not change (Zobel and Buijtenen, 1989). Research needs to prove that this explanation is happening, and if it is true, even more needs to be done about why this is occurring.

Although there is little explanation for what is occurring, the results are eye-opening. They show how the carbon is stored in the stem. High-ring-count trees may not be storing as much carbon in their rings as they once did. Carbon may be stored elsewhere, such as in the branches or needles.

Impact of PDSI from June through February of the next year on SG

PDSI, calculated using temperature, precipitation, and the available soil water content, is a common metric used to identify droughts or differentiate dry years from wet years (Palmer, 1965). The positive linear relationship between the average PDSI from June through February of the following year and SG suggests that when the soil gets wetter than usual, the SG increases. Basically, latewood growth occurs from June through December, then enters its dormant stage in the following January and February of the next year. It has been recorded that longleaf pine can skip its dormant phase and produce latewood until spring arrives for earlywood production (Rother et al., 2018). Why the dormant phase was skipped is not well understood, but the study did find that smaller trees tend to skip their dormant phase more than bigger trees. Many studies have found that an increase in available moisture during the latewood growth has caused an increase in latewood growth (Soule et al., 2021; Henderson and Grissino-Mayer, 2009; Zampieri et al., 2024). Therefore, it may be possible that the increase in moisture availability during its dormant months caused the tree to not become dormant and to continue to produce latewood instead. Hence, this addition of latewood caused the SG to increase.

To verify this, we created additional models, but only changing the PDSI months tested to see if the precipitation from the dormant months has an effect. It is important to note that four separate models had to be run as the PDSI variables are highly correlated with each other since their data overlaps. The model with the PDSI through the latewood production months (Juen through December) has the lowest coefficient but does have the lowest error as well. Yet, PDSI for June through January and June through February have the highest coefficients (with June through February being slightly higher) but had more error than June through December but less than PDSI. The annual PDSI had a higher coefficient that June through December but had the most error out of any of the models. The strongest positive relationship out of all four variables was the one that included the dormant months. Therefore, this supports our idea that an increase in available moisture during the dormant months may extend latewood growth and result in a higher SG. Although the variables with the dormant months included may not be the best fit for the data, the difference is minimal. Our results and current literature agree well from this perspective. More research directly relating to available moisture during dormant months and SG is needed to fully support this explanation.

For transparency, it is important to note that because the PDSI equation uses available water capacity of the soil as one of its variables, there is reasonable concern that they are correlated. Yet, the VIF (variable inflation factor) calculated for the model was 1.0, low enough to include it in the model. Additionally, the correlation might be lower than usual as the PDSI data were calculated at the county level and the difference in soil texture between sites was not included in the PDSI calculation. Therefore, the PDSI value and soil texture will be considered simultaneously in the model for understanding how moisture availability due to precipitation and temperature affects SG at a temporal scale.

Impact of very coarse sand on SG

The study sites in the Jones Center range from poorly drained clay soils to excessively drained sands (Stambaugh et al., 2021). The positive relationship between the proportion of very coarse sand and SG (Table 4) reflects the potential effect of soil texture on tree growth in general and SG specifically. The low available water capacity of coarse soil textures has been a limiting factor of tree growth (USDA Natural Resources Conservation, 2008), which may further affect wood SG values. The multiple linear regression model suggests that the impact of very coarse sand on SG may be related to the precipitation patterns throughout the months and how they differ. For summer months (months included in the latewood production), there are many more wet days and overall, more precipitation than the spring months (earlywood production period) (Rother et al., 2018) (Figure 9). It is well known that both earlywood and latewood growth have a positive relationship with precipitation during their growth months (Soule et al.,2021; Henderson et al.,2009; Zampieri et al. 2024). With the summer months being watered more frequently than the spring months, the latewood growth period may not experience as much loss of moisture availability as the earlywood production. Therefore, latewood growth will not be impacted by very coarse soil as much as earlywood. It may alter the ratio between the season wood, with earlywood growth being shortened and latewood growth not being affected. A higher percentage of latewood will have a higher SG value (Zobel and Buijtenen, 1989).

Although there is very strong evidence of why very coarse sand has a positive relationship with SG, it is important to note that this is a conflicting result with the first chapter, where SG and very coarse sand have a negative relationship from a regional perspective. At the regional level, more factors and interactions are correlated to SG. However, those factors did not appear in the regression model in this chapter. Furthermore, the interaction between PDSI and very coarse sand is not statistically significant. The apparent conflicting result is most likely related to the scale matter as found in many other ecological phenomena (Davies et al., 2017). More chronological research needs to be done in the future, unraveling the effect of spatial and temporal scales on such kinds of relationships and related mechanisms.

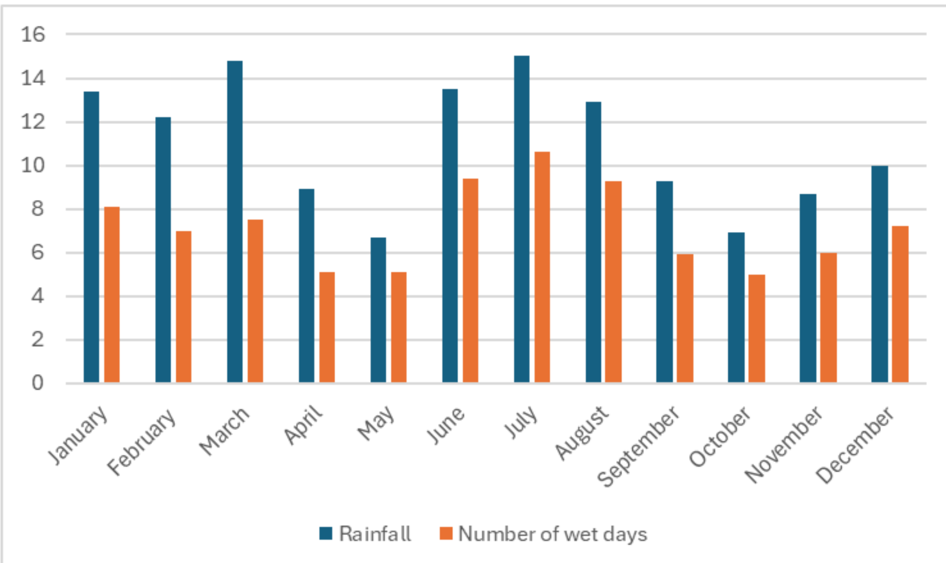

Figure 9.The number of wet days (rainfall larger or equal to .354 mm) and monthly precipitation for Camilla, GA (31.190°, -84.204°), which is about 15 miles from The Jones Center, GA. The data was taken from Dzotsi et al., 2014, which was originally from the National Climatic Data Center (Arguez et al., 2012).

Importance:

Along with the results from this study, there is more importance that this thesis contributes. First is that the variables were chosen based on information provided by dendrochronological studies, since the research on SG is very limited. Additionally, they were also used to explain the variables' influence as they provide information on latewood and earlywood growth, which is known to be a main control of SG. This thesis has proved that dendrochronological studies based on latewood and earlywood growth can be used to test against SG variables and could be directly linked to them as well. This is a very important contribution as there is an abundance of dendrochronology studies in the literature that can be used as guides for future SG studies.

These results are only the first step in this research. It was intentional that all the variables from this study were from open-source free data sources that cover the entire United States. This was done because with more samples and further evaluation, a predictive model can be made estimating SG based on its most influential factors. By using these extensive datasets, we could potentially estimate where the SG would be at any location. This could be an incredible tool for carbon markets as SG can be a loose indicator of carbon, as SG can be used to estimate biomass, which can be used to estimate carbon.

2.5. Conclusion:

Our study provides valuable information regarding the radial variation of SG after ring count 62 and the driving factors that impact radial variation. Our main finding was that after a ring count of 62, the SG decreases as the ring count increases. Additionally, it was found that PDSI from June to February has a positive relationship with SG. This indicates Longleaf Pine may skip dormancy and continue to produce latewood, causing the SG to increase. Although more research will be needed to confirm this, this result provides a new understanding of how climate change could impact the future SG of trees. It was also found that very coarse sand had a positive relationship with SG, even though the samples were taken from sites that are relatively close to one another. This enforces the importance of soil on SG and needs to be included when testing the temporal factors on SG. The temporal trend of SG sheds light on future dendrochronological studies to explore carbon dynamics and map the spatial distribution of longleaf pine forests' carbon stock based on tree age (ring count) and the relationships between climatic and soil variables and trees' SG.

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Appendix 1: Spatial Variation Chapter Variables

Climate Variables:

Latewood Formation Period:			
Min Month	Max Month	Climate Variables:	Description:
June	December	• Precipitation (mm) • Max VPD(hPa) • Average Temperature (°C) • Max Temperature (°C)	Latewood formation period used in Zampieri et al., 2024 and developed in Rother et al. 2018. This variable is the most accurate to represent the latewood growth period.
June	October	• Precipitation (mm) • Max VPD(hPa)	Found positive strong correlations between Palmer Drought Z-index and latewood growth (Stambaugh et al., 2021)
June	January of following year	• Precipitation (mm) • Max VPD(hPa)	Rother et al. 2018 stated that the latewood formation period is from June to

June	February of following year		December but found some trees did not go dormant in January or February and instead the latewood growth was extended during these months. The following year was used for January and February because the cores do not follow the calendar year and the dormancy or latewood production months bleed into the following year.

Seasons:			
Min Month	Max Month:	Climate Variables:	Description:
March	May	• Precipitation (mm) • Max VPD(hPa) • Max Temp (°C) (Only for Spring)	Henderson and Grissino-Mayer 2009 tested the climate data with tree growth by dividing the climate into the four seasons. Also, March through May is when earlywood growth formation is (Rother et al., 2018). Additional note, the January and February are the months of the following year and not the current.
June	August		
September	November		
December	February		

Overall Growing Season:			
Minium Month	Maximum Month	Climate Variables:	Description:
March	November	• Precipitation (mm) • Max VPD(hPa)	Haywood et al., 2015 used these months to represent the overall growing season for Longleaf Pine.

Other:		
Type:	Climate Variables:	Description:
Annual	• Mean Temperature (°C) • Max Temperature (°C) • Min Temperature (°C) • Precipitation (mm) • Max VPD(hPa) • Min VPD (hPa) • Temperature dewpoint (°C)	The average precipitation for the entire year was put into the model.
Monthly	• Precipitation (mm)	Every individual month was put into the model. This included the following years

	• Max VPD(hPa)	January and February since the cores do not follow our calendar year.

For the table above, the abbreviations are as follows max stands for maximum, min stands for minimum, and VPD stands for vapor pressure deficit.

Soil Data:

Variable Name	Definition provided by soil metadata (https://www.nrcs.usda.gov/sites/default/files/2022)	Unit
Available Water Capacity (awc_r)	The amount of water that an increment of soil depth, inclusive of fragments, can store that is available to plants. AWC is expressed as a volume fraction, and is commonly estimated as the difference between the water contents at 1/10 or 1/3 bar (field capacity) and 15 bars (permanent wilting point) tension and adjusted for salinity, and fragments	cm/cm
Organic Material (om_r)	The amount by weight of decomposed plant and animal residue expressed as a weight percentage of the less than 2 mm soil material	%
Coarse Sand (sandco_r)	Mineral particles 0.5mm to 1.0mm in equivalent diameter as a weight percentage of the less than 2 mm fraction.	%

Fine Sand (sandfine_r)	Mineral particles 0.10 to 0.25mm in equivalent diameter as a weight percentage of the less than 2 mm fraction.	%
Medium Sand (sandmed_r)	Mineral particles 0.25mm to 0.5mm in equivalent diameter as a weight percentage of the less than 2 mm fraction.	%
Total Sand (sandtotal_r)	Mineral particles 0.05mm to 2.0mm in equivalent diameter as a weight percentage of the less than 2 mm fraction.	%
Very Coarse Sand (sandvc_r)	Mineral particles 1.0mm to 2.0mm in equivalent diameter as a weight percentage of the less than 2 mm fraction	%
Very Fine Sand (sandvf_r)	Mineral particles 0.05 to 0.10mm in equivalent diameter as a weight percentage of the less than 2 mm fraction.	%
Total Clay (claytotal_r)	Mineral particles less than 0.002mm in equivalent diameter as a weight percentage of the less than 2.0mm fraction.	%
Coarse Silt (silt_co_r)	Mineral particles ranging in size from 0.02mm to 0.05mm in equivalent diameter as a weight percentage of the less than 2.0mm fraction.	%

Fine Silt (siltfine_r)	Mineral particles ranging in size from 0.002 to 0.02mm in equivalent diameter as a weight percentage of the less than 2.0mm fraction.	%
Total Silt (silttotal_r)	Mineral particles 0.002 to 0.05mm in equivalent diameter as a weight percentage of the less than 2.0mm fraction.	%

The following table lists the name of the soil as well as the abbreviated name used by the Web Soil Survey. The definitions described are directly from the metadata (Soil Survey Staff). For the abbreviations used in the table, cm stands for centimeter.

Other:

Type:	Description:
Cambial Age	The variable was calculated by counting the rings from pith to bark. It has been noted that the radial variation of a core is linked to specific gravity (Eberhardt and Samuelson, 2015, and Eberhardt et al., 2018).

Appendix 2: Temporal Chapter Variables Used:

All variables in Appendix 1 were also used in this chapter. But, there were some additional variables that were used in this chapter that were not used in the previous chapter and are listed below. The variables included here were not included in the other chapter as these variables did not significance or better variables were found. Yet, these were still induced in this chapter in case they became significant because even though these are not the best or well supported the variables, they may have significance that would be important to investigate.

Climate Variables:

Latewood Formation Period:			
Minium Month	Maximum Month	Climate Variables:	Description:
July	September	• Precipitation (mm) • Max VPD (hPa) • Max Temperature (°C) • Mean Temperature (°C)	Soulé et al. 2021 found that adjusted latewood growth had a positive relationship with precipitations from July to September.

PDSI:	
Type:	Reasoning:

Annual Average Monthly Average Average of June-January Average of June-February Average of June-December June through December PDSI variance	The Palmer Drought Index (PDSI) is a great indicator if a year was going drought a dry or wet spell. Therefore, by including this variable we can assess how SG reacts when the conditions are considered dryer or wetter compared to other years. This variable was not included in the other chapter as the variable on a smaller temporal scale. Therefore, by using it in the other chapter the variable would become too generalized.

Other metrics besides average		
Type:	Climate Variable	Reasoning:
Standard Deviation Variance	• PDSI • Precipitation (mm) • Average Temperature	Standard deviation and variance are important variables as inconsistency with climate variables may impact SG. These variables were not included in the other chapter because it may be too generalized of a variable and not have large impact.

Other:

Type:	Description	Reasoning:
Max distance from pith	This is the number of rings that the last ring year is from pith. For example, if the first ring is the year 1950 and the last ring year of the sample is 1970, then the max distance from pith is 20 rings.	The radial variation of a core is linked to specific gravity (Eberhardt and Samuelson, 2015, and Eberhardt et al., 2018).
Min Distance from pith	This is the number of rings that the first ring year is from pith. For example, if the first ring is the year 1950 and the first ring year of the sample is 1960, then the max distance from pith is 10 rings.	