# Factors Affecting Aboveground Carbon Storage in Mixed Oak-Pine Forests: A Multiple Regression Analysis of Southeastern U.S. Forest Inventory Data

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**Abstract**

This study investigated the factors affecting aboveground carbon storage in mixed oak-pine forests of the southeastern United States, with a particular focus on the influence of stand age. Using data from 946 Forest Inventory and Analysis (FIA) plots collected from 2009 to 2019, a multiple regression analysis was conducted to determine the relative importance of various forest and topographic variables on carbon sequestration. After data cleaning and model validation, results indicated that basal area (a proxy for stand age) was the most significant predictor of carbon storage, showing a strong positive relationship. Tree density demonstrated a significant negative relationship, while species diversity and structural diversity both showed positive but less influential relationships with carbon storage. The logarithmically transformed model explained 97.6% of the variance in carbon storage, with minimal overfitting confirmed through cross-validation. These findings provide valuable guidance for forest managers seeking to optimize carbon sequestration in southeastern oak-pine ecosystems. Management strategies should prioritize the maintenance of mature stands while controlling tree density to reduce competition. Additionally, promoting both species and structural diversity at intermediate levels could enhance carbon storage capacity, potentially increasing the role these forests play in regional climate mitigation efforts.

**Part 1: Literature Review**

**Purpose**: The relationship between tree diversity and carbon sequestration in forest ecosystems is a critical area of research, especially as climate change worsens and solutions to mitigate it become more urgent. This literature review will examine three peer-reviewed articles that investigate the relationships between tree diversity metrics, stand characteristics, and carbon storage in forest ecosystems, particularly in the mixed oak-pine forests in southeastern United States. For some background, trees, like other plants, take in carbon dioxide as they photosynthesize. They transform this carbon dioxide into sugars to use for growth and functional purposes. Because of this, trees can store massive amounts of carbon, making them biologically and culturally important as carbon dioxide emissions continue to increase and contribute to global warming through the greenhouse effect. It is important to understand the factors that can contribute to carbon storage in forests, therefore, as forest managers can then increase carbon sequestration in trees by applying effective strategies.

Fatunsin and Naka (2025) determined how structural and species diversity in mixed oak-pine forests of the southeastern United States can affect the carbon storage capacity of trees. The authors hypothesized that increased species diversity and structural diversity[1] would increase resource usage and ecosystem functions, therefore leading to higher carbon storage. The sample consisted of data from 946 Forest Inventory and Analysis (FIA) plots located in oak-pine forests across Florida, Georgia, and Alabama from 2009 to 2019. The researchers analyzed aboveground carbon storage (from tree biomass), tree diameter, basal area[2], species identification, functional dominance[3], functional divergence[4], mean annual temperature, annual precipitation, elevation, stand age[5], tree density, and geographic location coordinates. The authors used a structural equation modeling (SEM) approach to test the cause-effect relationships between multiple variables, statistically controlled for climate variables that might confound relationships, analyzed the interaction effects between environmental variables and diversity to determine how the relationships fit into the context of each forest, and validated their model and conducted goodness-of-fit testing to ensure reliable results. The study concluded that structural and species diversity had a positive relationship with carbon storage, but structural diversity was a stronger predictor. Annual temperatures had a negative effect on carbon storage, but annual precipitation showed a positive relationship with it. Elevation also had a positive relationship with carbon storage, likely due to higher species diversity at higher elevations. Overall, the researchers concluded that high structural diversity increases carbon storage in mixed oak-pine forests in this region, supporting their hypothesis. However, this study did not reveal much about how functional traits of trees contribute to carbon storage, nor strongly consider temporal factors in their results.

[1]Structural diversity is the variety in the different types and sizes of vegetation in a forest in the vertical and horizontal dimensions, including canopy structure, tree heights, shrubs, and deadwood.

[2]Basal area (Figure 1) is the cross-sectional area of a tree at a height of 4 ½ feet from the ground level.

[3]Functional dominance is the impact of a few dominant traits on an ecosystem’s functioning.

[4]Functional divergence is the degree to which different species exhibit differences in their functional traits.

[5]Stand age is the average age (mean age at breast height, 4.5 feet) of the trees within a particular area, or stand.

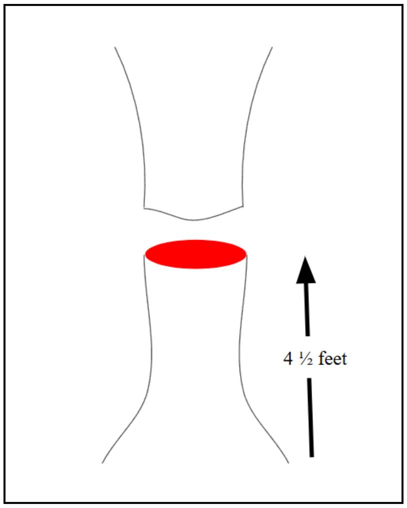


Figure 1. Shah, N. (2025). *Basal Area of a Tree*. Created on Google Slideshow.

In another study, researchers observed and compared multiple forest types to understand how carbon storage differs across forest strata (Ullah et al., 2024). They used structural equation modeling (SEM) to understand relationships between forest layers, carbon storage, and other involved variables. The sample consisted of inventory data from mixed forests, two types of broad-leaved forests, and coniferous forests, from East Asia. The researchers measured carbon storage for herb layers, shrub layers, and overstory, diameter at breast height (DBH), height, maximum height, stem density[1], basal area, elevation, canopy openness, Shannon diversity[2], Simpson diversity[3], Pielou's evenness metric[4], branch, leaf, and stem biomass, and other environmental variables for each forest. They compared standardized path coefficients between models to determine the relative strength of relationships and assess whether diversity-carbon patterns were consistent across forestry types with statistical analysis using chi-squared tests, comparative fit indices, and root mean square error of approximation. The study revealed that tree species diversity influenced understory carbon storage more than overstory carbon storage in all the forest types. Forest type and elevation explained lots of variability in overstory carbon storage, and stand factors like DBH and basal area had moderate influence. Tree species diversity interestingly had a negative relationship with overstory carbon in the SEM, but positively affected understory ecosystem function. However, because this study used cross-sectional, rather than long-term data, it overlooked temporal relationships, which are especially important in the context of forests' slow growth. The study also did not extensively examine how functional traits of trees can explain the differences in carbon storage between the overstory and understory.

[1]Stem density is the number of tree stems (of any type) per unit of area (typically a hectare).

[2]Shannon diversity is a measure of species diversity within a given community (Eq. 1). It considers species richness and evenness.

[3]Simpson diversity is a measure of biodiversity that is based on the probability that two randomly selected individuals from a sample will belong to different species (Eq. 2). It is sensitive to dominant species.

[4]Pielou's evenness metric quantifies how evenly different species are represented in a community.

$$H = -\sum p_i ln(p_i)$$

Equation 1. Shannon diversity, where $p_i$ is the proportion of each species in the community.

$$D = 1 - ((\sum n(n-1))/(N(N-1)))$$

Equation 2. Simpson diversity, where n is the number of organisms of a species and N is the number of organisms of all species.

$$J = -\sum p_i ln(p_i) / \ln(S)$$

Equation 3. Pielou's eveness metric, where $p_i$ is the proportion of each species in the community and S is the total number of species.

Finally, Crockett et al., (2023) further characterized the relationship between structural diversity, species diversity, and aboveground carbon storage in United States forests using NASA's Global Ecosystem Dynamics Investigation (GEDI) lidar data *and* FIA plot data. The study was observational and examined the relationship between forest diversity and carbon storage on a huge spatial scale, so the researchers could determine patterns in several types of forests across the country. The sample was 1,796 forest inventory plots across the mainland United States, including broadleaf, coniferous, and mixed forests. The researchers analyzed aboveground carbon storage (from tree biomass), structural diversity based on GEDI (foliage height diversity) and inventory data (height and DBH diversity), species richness and other diversity indices, 3-D forest canopy structure using GEDI, climate variables, and forest types. To analyze this data, the researchers compared correlation strengths between carbon storage and structural diversity versus species diversity, while controlling for environmental factors. The study found that both GEDI and ground-based measurements of structural diversity produced a higher correlation with carbon storage than species diversity. Interestingly, the researchers found that the mechanisms underneath the increased carbon sequestration from higher structural diversity varied based on forest type. Broadleaf and coniferous trees created different forest architectures due to their different crown shapes and branching patterns. This study was able to infer cause-effect relationships because of extensive functional analysis on stem biomass accumulation rates and light absorption. In broadleaf forests, structural diversity increased carbon storage because of canopy packing. Essentially, trees of different heights and crowns filled different vertical niches, allowing for maximized light interception and increased photosynthesis. In coniferous forests, the crown shapes are conical and more consistent; therefore, the size distribution and spacing diversity was more influential to carbon storage. The researchers also discovered that structural diversity influenced carbon storage the most in mixed (both broadleaf and coniferous) forests because of vertical and horizontal niches being filled simultaneously. The GEDI lidar data revealed that more structural diversity in a forest led to 15-25% more canopy space filled, which was measured based on 3-D canopy space utilization. The researchers also determined that structural diversity had the strongest effects on carbon storage at intermediate levels, with diminishing returns at very high structural diversity, suggesting that forest managers should manage the structural diversity in a forest accordingly to optimize carbon sequestration. Another result of this study was that the remote sensing data was just as effective as ground-based inventories for forest carbon assessment, suggesting that researchers in the future can take advantage of this less labor-intensive method of research. Overall, although this study covered many samples over a large land area, certain forest types were underrepresented due to the scope. Further, the remote sensing approach, while effective in this context, could have many limitations for studies related to forest understories.

Evidently, structural diversity is very important to maximize carbon storage in forests. However, when forest managers look at oak-pine forests in the southeast of the United States specifically, they must understand how carbon storage can be maximized so they can vary the structural diversity based on the topographic conditions. In addition, to address how many similar studies have not considered temporal variables, basal area will be used as a proxy for tree age to determine if stand development age can affect the relationship between structural diversity and carbon storage as forests mature. Therefore, this paper will answer the following questions:

1. Besides structural diversity, what other topographic and/or forest variables can affect carbon storage in oak-pine forests in the southeastern United States?
2. Does accounting for temporal variables, such as stand age (through basal area) make a significant difference in carbon storage in oak-pine forests in the southeastern United States?

**Part 2: Methods, Results, and Discussion**

**Sample**

The dataset (Table 1) used consists of manipulated data from 946 Forest Inventory and Analysis (FIA) plots from 2009 to 2019. The FIA plots span the humid subtropical forest regions of the southeastern U.S. (Figure 2). The dataset was published on 2025-5-19. FIA uses a standardized sampling approach, where one plot every 2428 ha is analyzed and the plot size is 0.067 ha, comprising four circular subplots spaced 36.6 m apart from each other. The oak-pine forests included Virginia pine/southern red oak, loblolly pine/hardwoods, slash pine/hardwoods, eastern white pine/northern red oak/white ash, eastern redcedar/hardwoods, longleaf pine/oak, shortleaf pine/oak, and other pine/hardwood.

| plotid | Height | Tree density | Structural Shannon diversity | Species Shannon diversity | Basal area | Carbon storage | Mean slope | Elevation | Temp. | Precipitation |
|---|---|---|---|---|---|---|---|---|---|---|
| 1_3_13_77 | 17.596872 | 14.92537 | 0.4258484 | 0.5566469 | 0.1940299 | 0.2115494 | 12.0000000 | 112.8 | 18.114 | 1484.718 |
| 1_4_57_16 | 16.679381 | 14.92537 | 0.9002561 | 1.3862944 | 0.2388060 | 0.5599325 | 12.0000000 | 146.3 | 16.519 | 1493.588 |
| 1_3_13_31 | 25.562992 | 14.92537 | 0.5623351 | 1.3208883 | 0.2686567 | 0.3530986 | 17.0000000 | 109.7 | 18.379 | 1469.641 |

Table 1. First 4 rows of cleaned dataset. Note: Table is altered by the author to display only variables relevant to the research question with modified names for clarity.


Figure 2. Fatunsin, O. E. (2025). Geographic range of FIA plots used for this study [N: 39.466, S: 24.3963, E: -75.2423, W: -106.6456.]. Dataset on tree diversity metrics and aboveground carbon storage in Southeastern U.S. oak-pine forests, 2009–2019. *Environmental Data Initiative*. https://doi.org/10.6073/pasta/493d42b6a6da266867054f90dc15deba

**Procedure**

Biomass estimates were obtained from FIA data. National-Scale Volume and Biomass Equations were used to calculate carbon storage and biomass from aboveground and belowground estimates included in the FIA data. Temperature and precipitation from 1991-2020 were gathered from datasets from the PRISM Climate Group. Shannon diversity was calculated for both species and structure with a class-width of 5 cm for small-diameter trees and 10 cm for larger trees. All other data and variables were obtained from filtering already available FIA data for forest type, climate type, and location.

**Data Cleaning and Exploratory Data Analysis**

After downloading an available cleaned version of the dataset from the *Environmental Data Initative* (USGS, 1998), the data was opened in RStudio. The tidyverse, leaps, knitr, kableExtra, car, and caret library were used for all statistical analysis in this study. To understand the data, summary statistics were first generated for the variables of interest (Table 2). Then, histograms were created to examine the distribution of data (Figure 3). Then, to visualize each variable's relationship with carbon storage, pairwise relationship diagrams (Figure 4) and correlation matrices (Figure 5) were created.

| Variable | Min | 1st Qu. | Median | Mean | 3rd Qu. | Max |
|---|---|---|---|---|---|---|
| Basal area ($m^2$/ha) | 0.194 | 5.164 | 10.664 | 12.085 | 17.757 | 47.791 |
| Height (CV, m) | 1.332 | 18.322 | 23.635 | 24.367 | 29.315 | 98.200 |
| Tree density (trees/ha) | 14.93 | 119.40 | 223.88 | 257.69 | 373.13 | 910.45 |
| Slope (°) | 0.000 | 0.000 | 5.101 | 8.418 | 12.000 | 48.311 |
| Elevation (m) | 0.0 | 30.5 | 76.2 | 103.7 | 155.4 | 435.9 |
| Species Shannon index | 0.000 | 1.012 | 1.394 | 1.334 | 1.741 | 2.566 |
| Size Shannon index | 0.000 | 1.099 | 1.416 | 1.336 | 1.627 | 2.206 |
| Temperature (°C) | 14.09 | 14.09 | 18.37 | 18.56 | 19.73 | 25.52 |
| Precipitation (mm) | 1144 | 1373 | 1434 | 1445 | 1503 | 1767 |

Table 2. Summary statistics for all variables of interest.

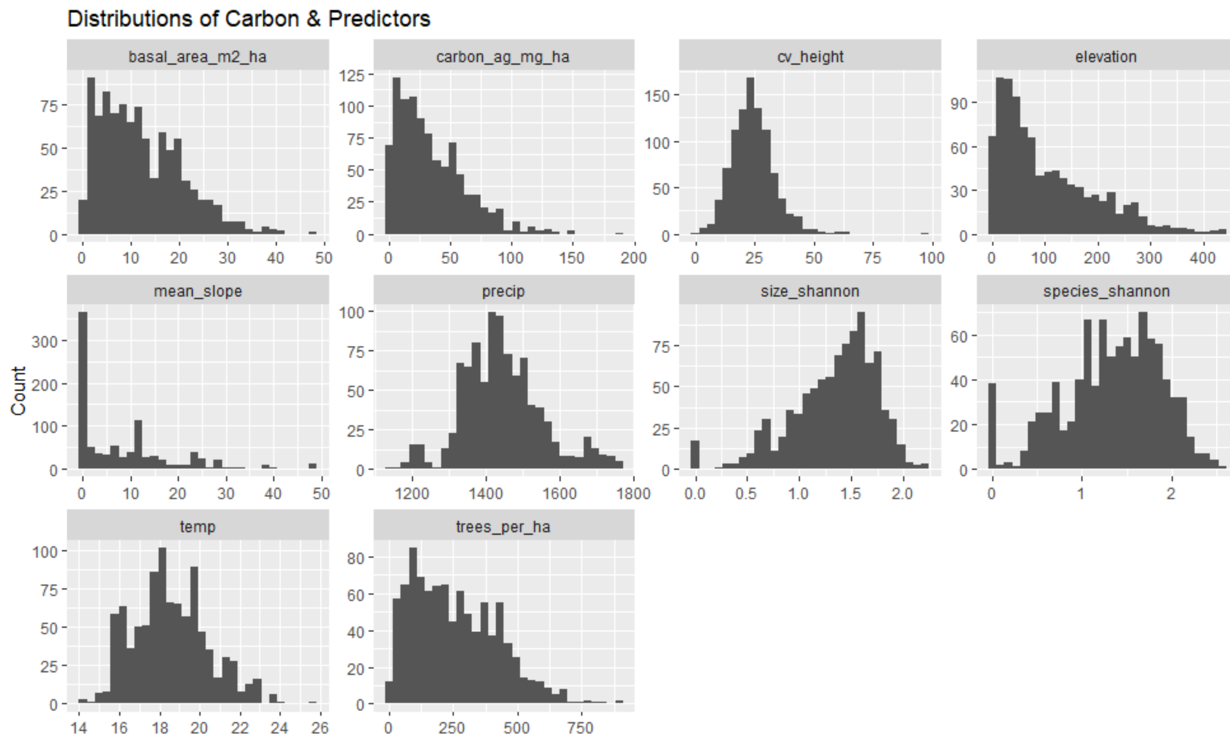


Figure 3. Histograms of variables of interest.

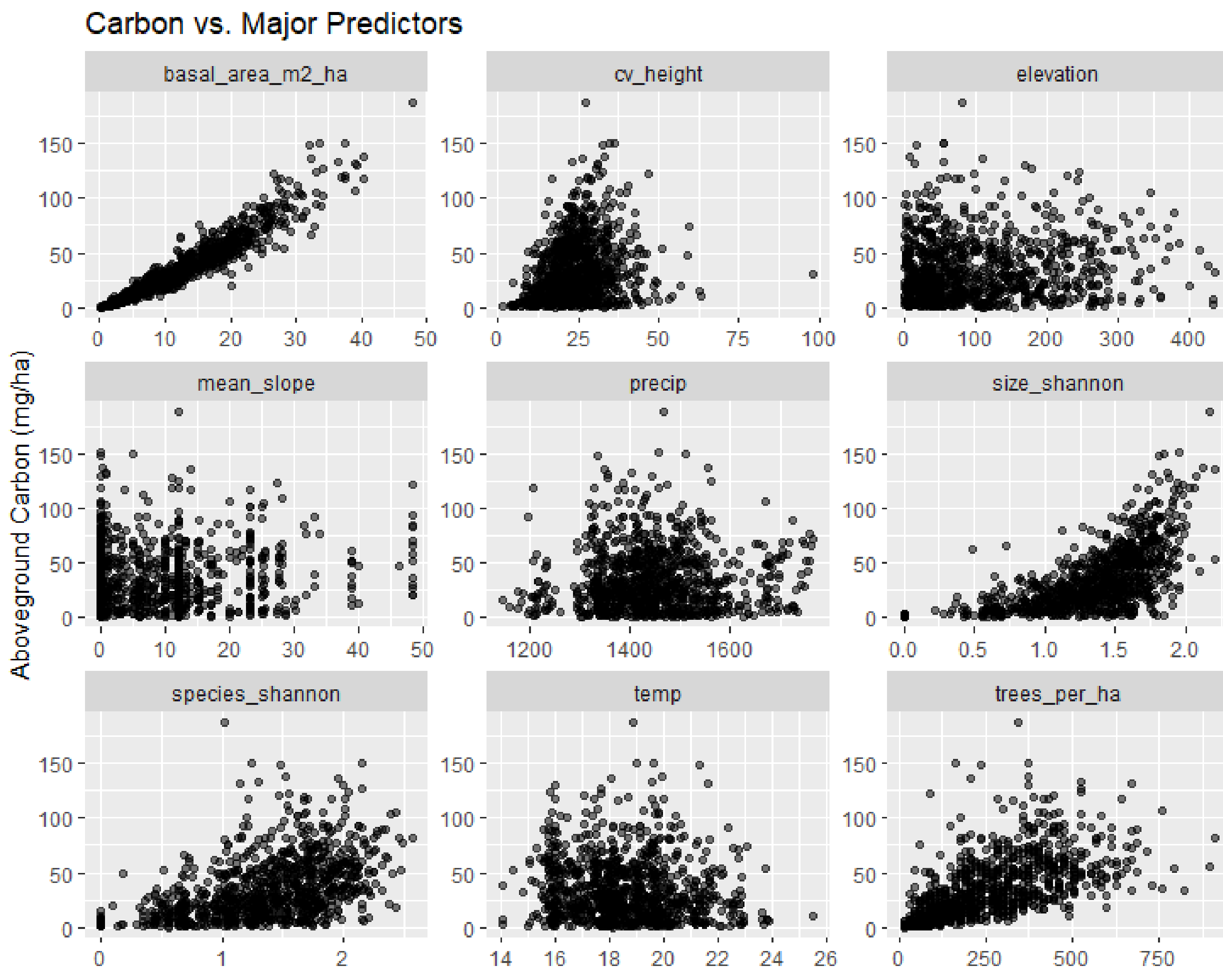


Figure 4. Pairwise relationships of each variable of interest with the dependent variable, aboveground carbon storage.

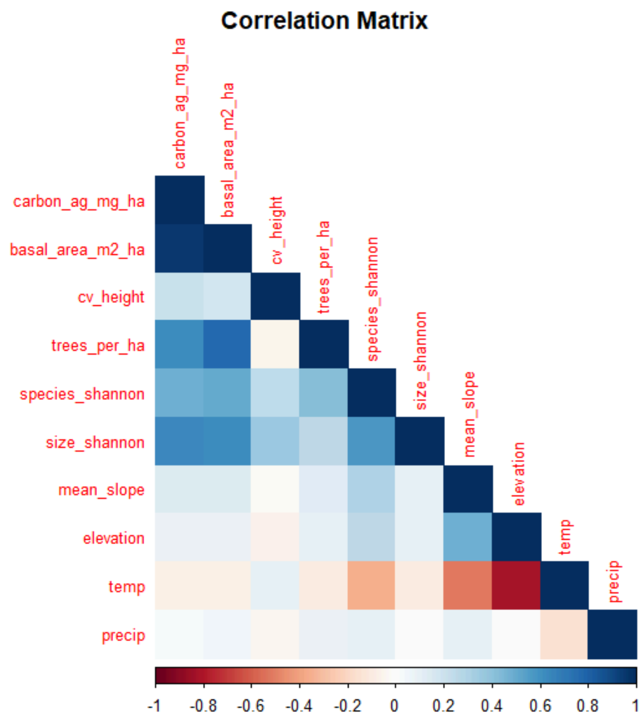


Figure 5. Correlation matrix of each variable of interest with each other.

## Fitting the Model

After exploring and visualizing the data to better understand structure, the regsubsets function from the leaps library was used to perform a best subsets selection in a linear regression format of a model using all possible variables of interest to predict carbon storage. The results of the best subsets selection were that basal area was the most important predictor, followed by tree density, then height, then species diversity, then structural diversity, followed by temperature, precipitation, and elevation as the least important predictors (Figure 6). After determining these predictors, the lm function was used for an initial linear model. The output, shown in Table 3, had an adjusted R-squared value of 0.951.

| # Preds | (Intercept) | basalarea | height | treedensity | slope | elevation | shannon_species | shannon_structural | temp | precip |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | * | * | | | | | | | | |
| 2 | * | * | | * | | | | | | |
| 3 | * | * | * | * | | | | | | |
| 4 | * | * | * | * | | | * | | | |
| 5 | * | * | * | * | | | * | * | | |
| 6 | * | * | * | * | | | * | * | * | |
| 7 | * | * | * | * | | | * | * | * | * |
| 8 | * | * | * | * | | * | * | * | * | * |

Figure 6. Output of best subset selection on the linear model.

| Coefficients: | Estimate | Std. Error | t value | Pr(>\|t\|) | Significance |
|---|---|---|---|---|---|
| (Intercept) | 2.86 | 0.953 | 3.00 | 0.002740 | ** |
| basalarea | 4.17 | 0.052 | 79.46 | < 2e-16 | *** |
| height | -0.09 | 0.025 | -3.64 | 0.000284 | *** |
| treedensity | -0.06 | 0.002 | -25.39 | < 2e-16 | *** |
| shannon_species | 1.74 | 0.489 | 3.55 | 0.000400 | *** |
| shannon_structural | -2.73 | 0.795 | -3.43 | 0.000632 | *** |
| Residual standard error | 6.309 on 940 degrees of freedom | | | | |
| Multiple R-squared | 0.9512 | | Adjusted R-squared | 0.951 | |
| F-statistic | 3666 on 5 and 940 DF | | p-value | < 2.2e-16 | |

Table 3. Output of initial linear regression. Note that 0 corresponds to *** and 0.001 corresponds to **.

**Determining the Influence of Stand Age**

To answer one of the research questions, an F-test was then run to determine whether the addition of basal area, a method of determining stand age in trees, was a significant influence in the model. The F-test was run on a model with basalarea as a predictor and a model without basalarea as a predictor. The output, shown in Table 4, demonstrates that the addition of basal area into the model was significant ($p < 2.2e-16$), meaning that stand age is a statistically significant predictor of carbon storage in southeastern U.S. oak-pine forests.

| Res. Df | RSS | Df | Sum of Sq | F | Pr(>F) | Significance |
|---|---|---|---|---|---|---|
| 941 | 288677 | - | - | - | - | - |
| 940 | 37412 | 1 | 251265 | 6313.1 | < 2.2e-16 | *** |

Table 4. Output of F-test comparing a model with basalarea and a model without basalarea as a predictor. Note that *** is a significance code of 0.

**Checking Conditions**

Next, to determine the validity of the linear model created, conditions had to be checked. A histogram of residuals was generated to visualize the distribution of residuals (Figure 7), a residuals vs. fitted values plot was generated to determine if homoscedasticity was met (Figure 8), and a Normal Q-Q plot was constructed to examine the normality of the residuals (Figure 9). Evidently, although the distribution of the residuals might appear relatively normal in the histogram, the Normal Q-Q plot reveals that this condition is not upheld. The lower end and higher end of values demonstrate skew and indicate that a transformation is needed. Furthermore, the residuals vs. fitted values plot shows that the condition of homoscedasticity is not met, and that further transformations need to be done on the model for this condition to be met.

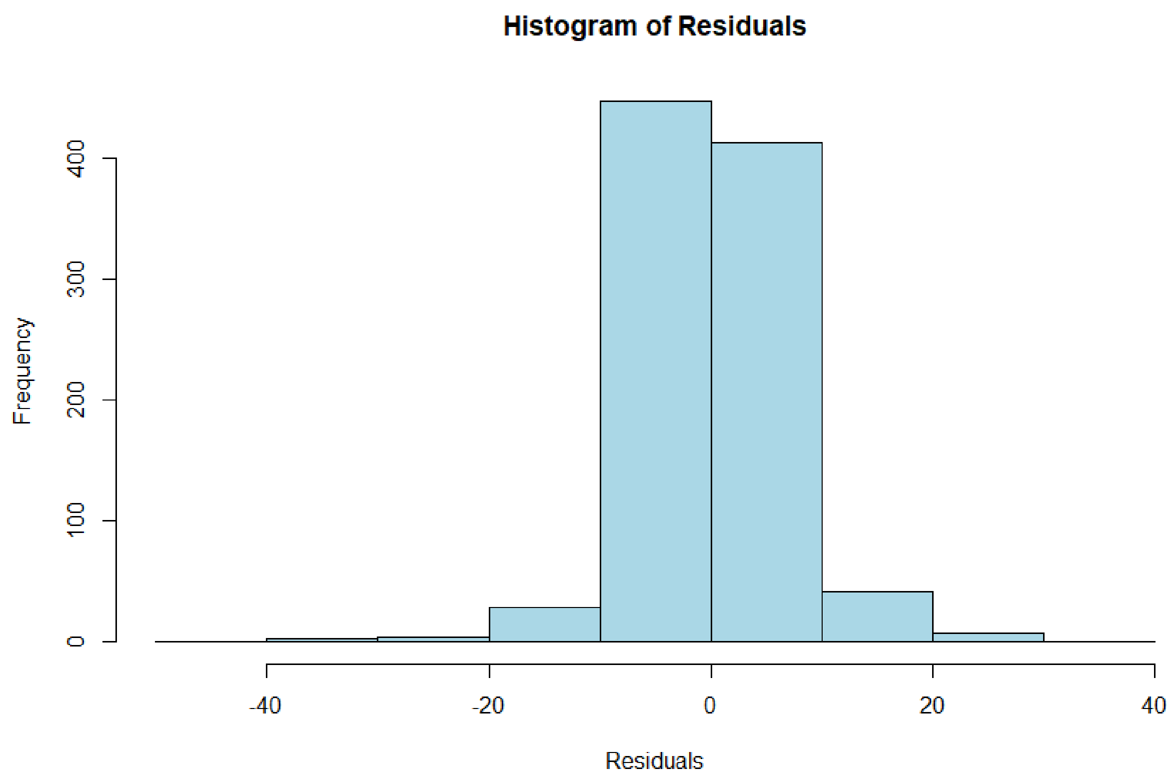


Figure 7. Histogram of residuals of initial model.

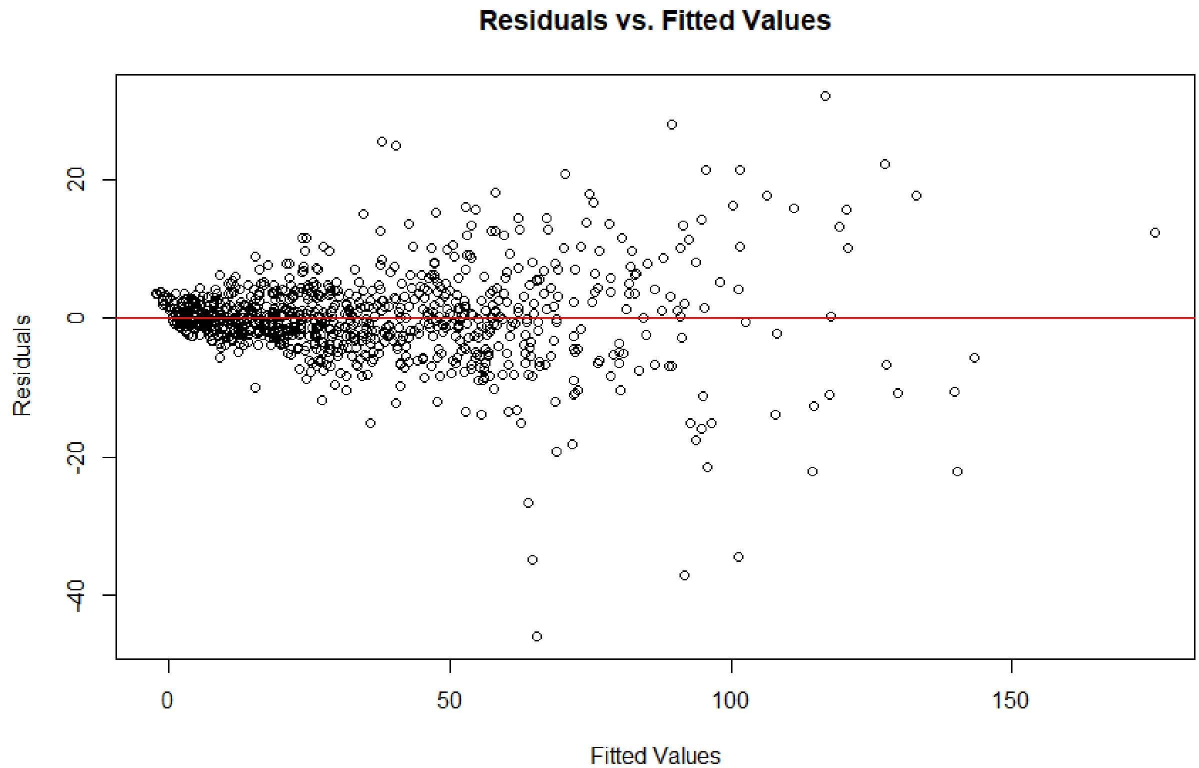


Figure 8. Residuals vs. Fitted Values plot of the initial model.

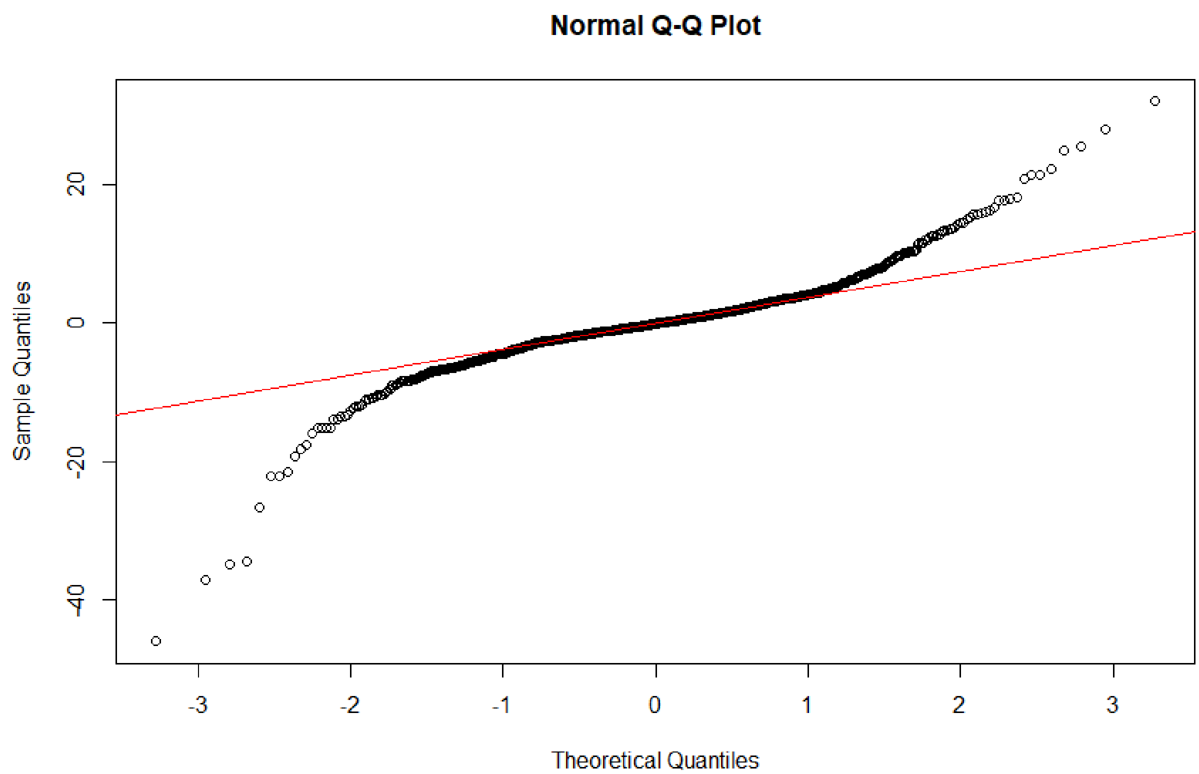


Figure 9. Normal Q-Q plot of residuals of initial model.

**Transforming the Model**

First, a logarithm transformation was applied on the dependent variable, carbon storage, to help the model achieve homoscedasticity. Then, to help mitigate the non-normality of the residuals, a logarithm transformation was applied to the three most influential predictors—basal area, height, and tree density. Note that many transformations were tested, including a square root transformation on the dependent variable and polynomial transformations on the independent variables, but the best approach based on residual vs. fitted values plots and normal Q-Q plots was the logarithmic transformation on the dependent and independent variables. The conditions of this new model were then tested and shown in Figures 10 and 11. The conditions were improved, but had not been fully met. There were still some unequal variances of the residuals and non-linearity of the normal Q-Q plot. As Table 5 demonstrates, a summary of this model revealed an adjusted R-squared of 0.972, an increase from the initial model. It also revealed that log(height) was no longer a significant predictor. However, after testing removing it from the model, the adjusted R-squared decreased, so it was chosen to remain. In addition, an ANOVA of the model (Table 5) also showed that the p-value of the overall model, < 2e-16, was statistically significant.

| Coefficients: | Estimate | Std. Error | t value | Pr(>\|t\|) | Significance |
|---|---|---|---|---|---|
| (Intercept) | 1.729558 | 0.090090 | 19.198 | < 2e-16 | *** |
| log(basalarea) | 1.357321 | 0.017192 | 78.953 | < 2e-16 | *** |
| log(height) | -0.008274 | 0.017049 | -0.485 | 0.62757 | |
| log(treedensity) | -0.330457 | 0.016955 | -19.491 | < 2e-16 | *** |
| shannon_species | 0.072340 | 0.014509 | 4.986 | 7.34e-07 | *** |
| shannon_structural | 0.083200 | 0.024347 | 3.417 | 0.00066 | *** |
| Residual standard error | 0.1846 on 940 degrees of freedom | | | | |
| Multiple R-squared | 0.9721 | | Adjusted R-squared | 0.972 | |
| F-statistic | 6555 on 5 and 940 DF | | p-value | < 2.2e-16 | |

Table 5. Output of ANOVA test on the model with a logarithmic transformation on the dependent and independent variables.

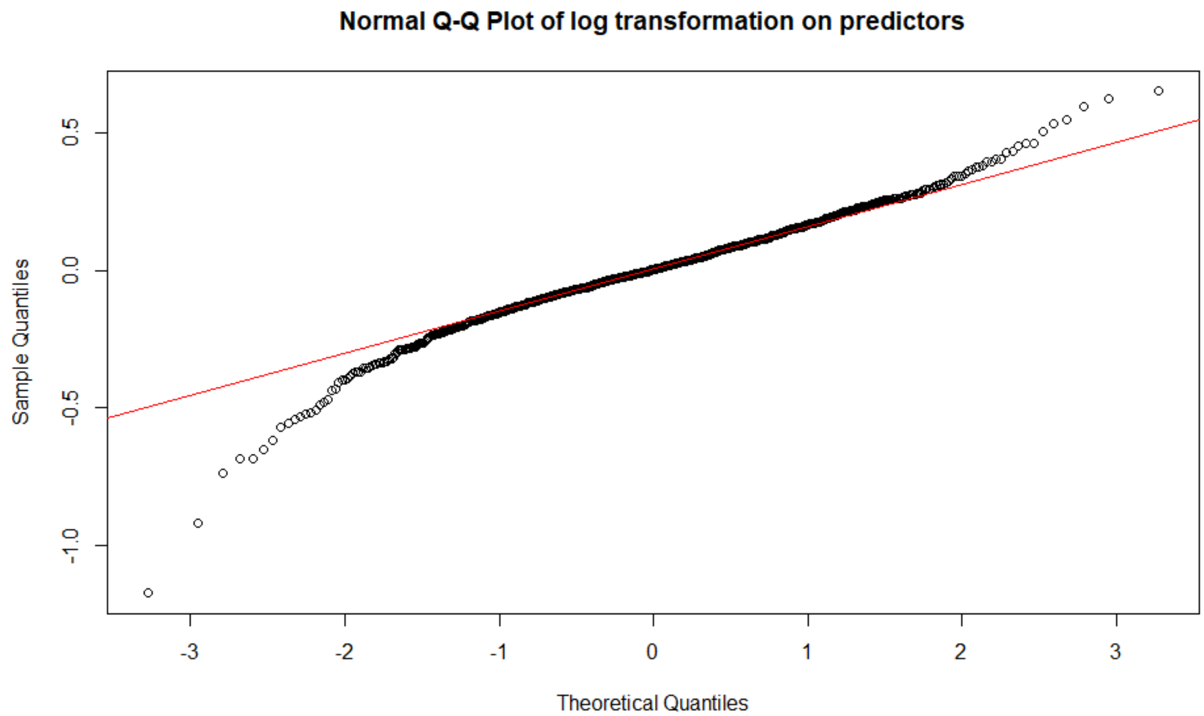


Figure 10. Normal Q-Q plot of logarithmic transformation on carbon storage and the main predictors.

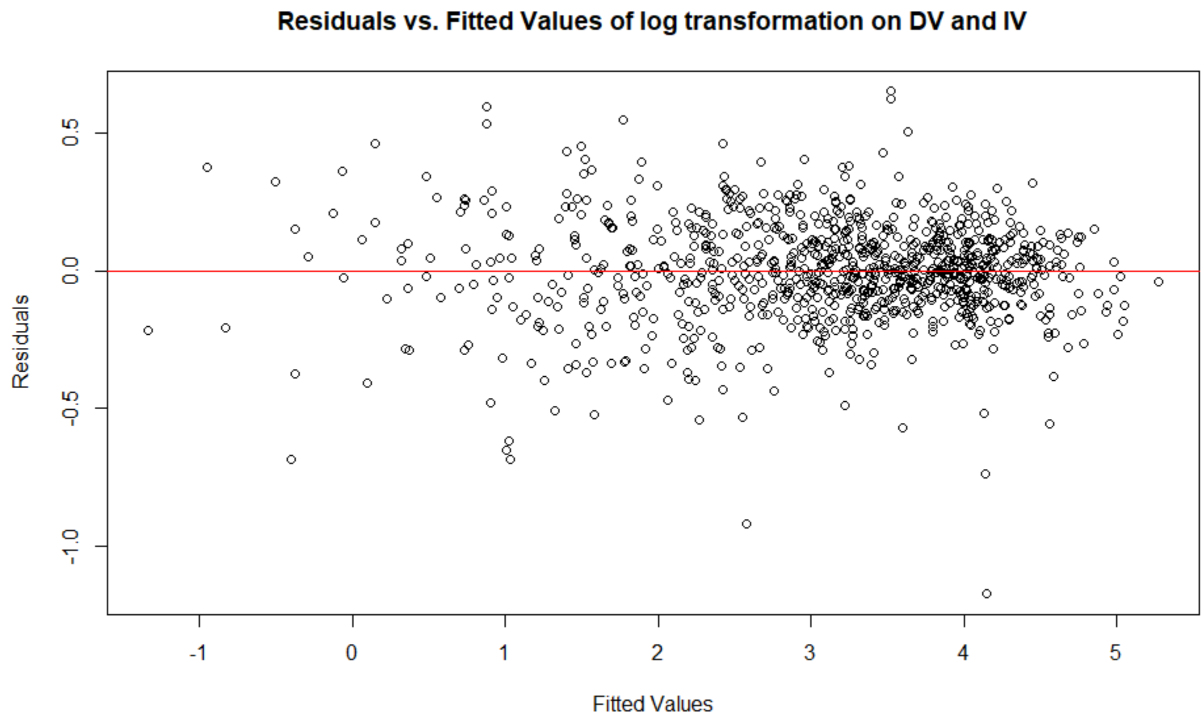


Figure 11. Residuals vs. Fitted values of the model with a logarithmic transformation on carbon storage and the three main predictors.

**Outlier Analysis**

Since the conditions of the transformed model were still not fully met, outliers were checked with three main methods: examining studentized residuals, leverage, and Cook's distance. First, studentized residuals were calculated and it was determined that there were 46 entries with studentizes residuals over 2 and 13 of those had a residual over 3. Then, moderate leverage and high leverage bounds were calculated (Equations 4 and 5) and compared to the leverage of all 946 entries. It was determined that 36 of the entries had a leverage higher than the high leverage bound, and 92 had a leverage higher than the moderate bound. Then, Cook's Distance was calculated and it was found that there were 68 entries with concerning Cook's Distance values.

Finally, to determine which entries to remove from the dataset, a function was created that flagged values which either had a studentized residual over 3, a high leverage, or a concerning Cook's Distance. Each entry that had 2 or more flags was removed from the dataset.

$$2 * p/n$$

Equation 4. Calculation for moderate leverage, where n is the number of observations in the dataset and p is the number of predictors in the model.

$$3 * p/n$$

Equation 5. Calculation for moderate leverage, where n is the number of observations in the dataset and p is the number of predictors in the model.

After cleaning the dataset, conditions were once more checked. A histogram of residuals was generated (Figure 12) which demonstrated a much more normal distribution, indicating that this condition has been better met. Then, a residuals vs. fitted values plot was generated, which shows a much more random distribution of residuals along the horizontal y=0 line (Figure 13), indicating that the condition of homoscedasticity has been better met. A normal Q-Q plot was created (Figure 14) that demonstrated much greater linearity than Figure 9 and Figure 10, which were generated with the dataset before outliers were removed. Another condition to test is multicollinearity, which was tested using the variance inflation factor (VIF) with the car package. The output, shown in Table 6, demonstrated that there was a moderate degree of collinearity with basal area and tree density, but nothing concerning, and no concerning collinearity with the rest of the variables. However, the correlations from Figure 5 indicate that multicollinearity is not a significant problem with these variables that would invalidate the model. Finally, because of the nature of the data (cross-sectional with independent plots and random sampling), there are no problems with the condition of independence.

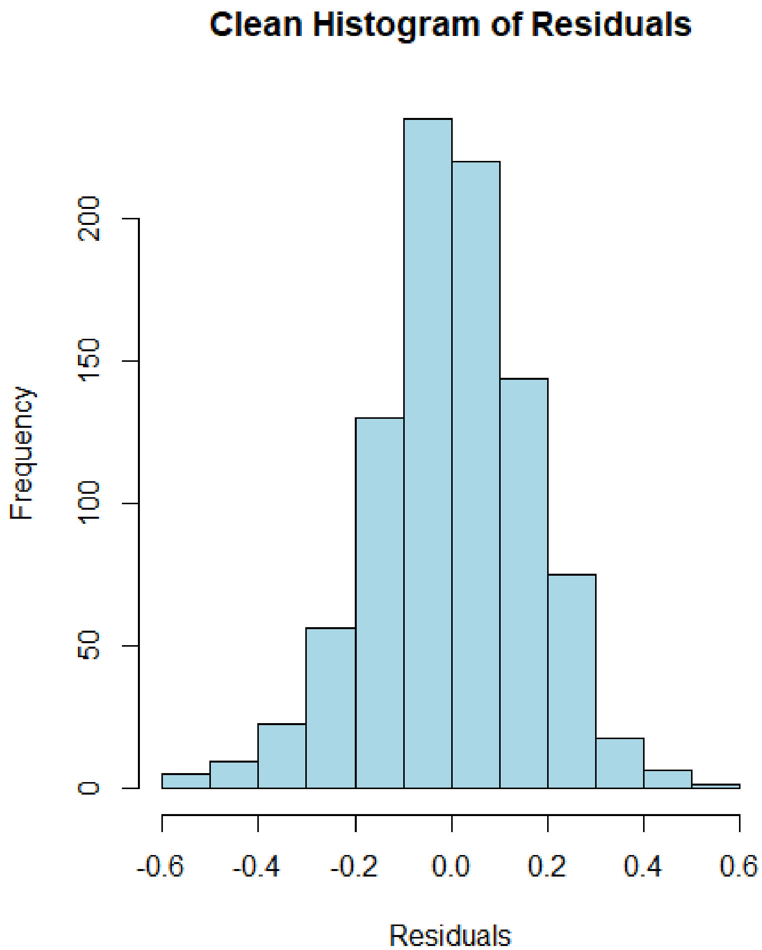


Figure 12. Histogram of residuals from final linear model.

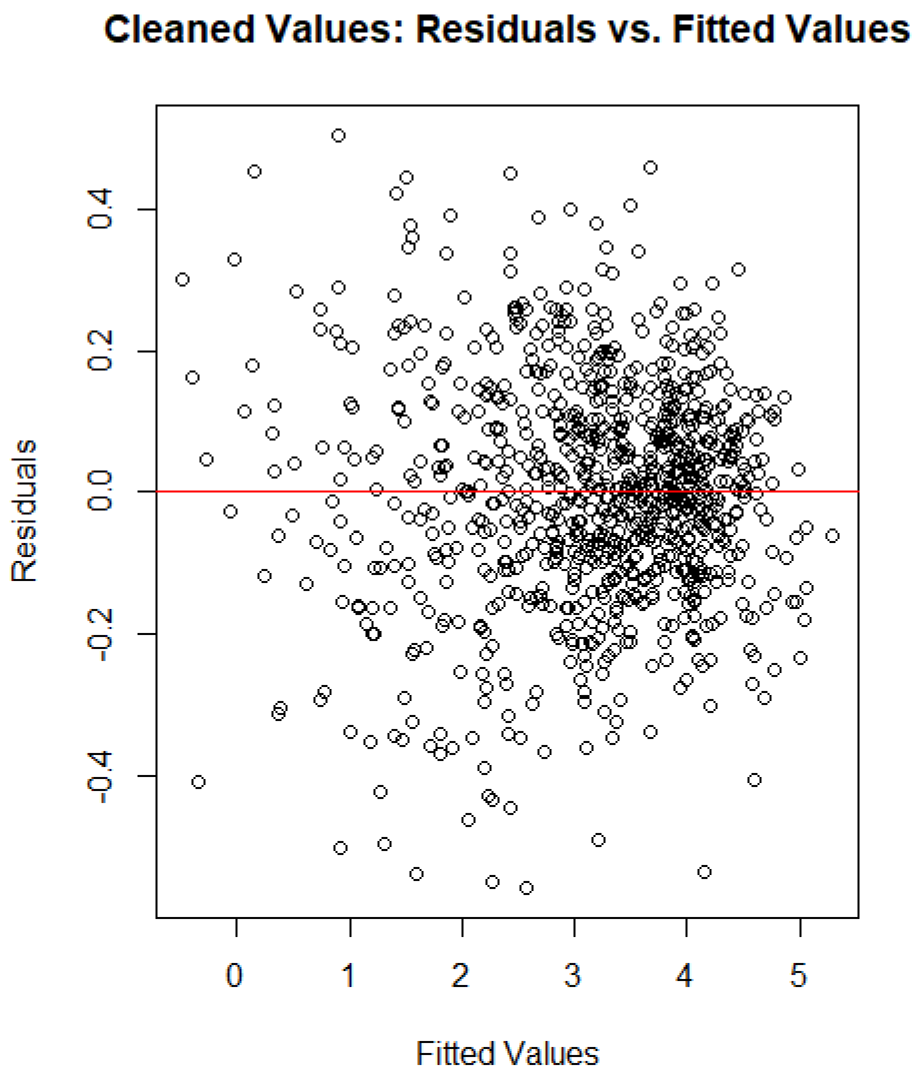


Figure 13. Residuals vs. Fitted Values plot of final linear model.

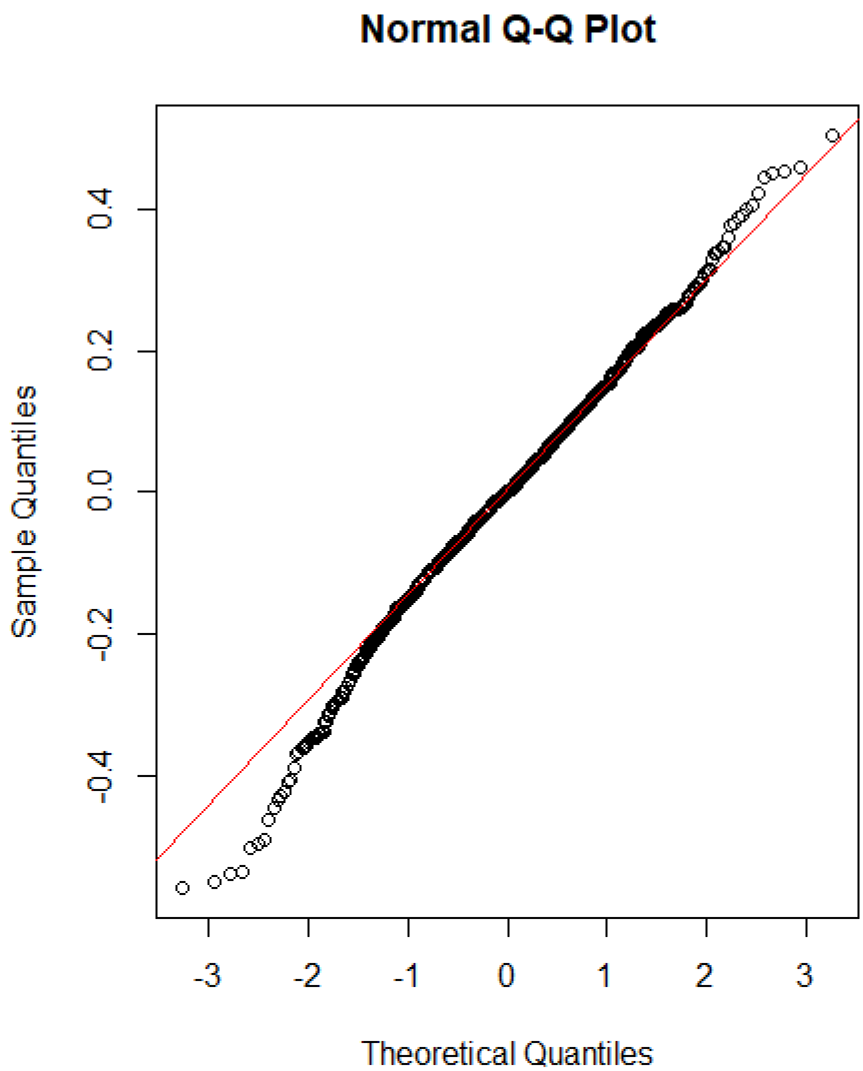


Figure 14. Normal Q-Q Plot of final linear model.

| | log(basalarea) | log(height) | log(treedensity) | shannon_species | shannon_structural |
|---|---|---|---|---|---|
| VIF | 7.007231 | 1.384797 | 5.164391 | 1.759835 | 2.775183 |

Table 6. VIF of all predictors in the final model using the cleaned dataset.

**Significance Test and Confidence Intervals**

After determining the equation for the final model, an ANOVA was conducted to determine the strength of the model. The results, shown in Table 7, demonstrate that removing the outliers improved the strength of the model to an adjusted R-squared of 0.9758. The p-value remained near 0, $p < 2.2e-16$. Then, 95% confidence intervals were generated for the coefficients on each of the variables of the model. The results, shown in Table 8, are mainly very small intervals, demonstrating that the variability of the model was reduced significantly with the transformation and removal of outliers.

| Coefficients: | Estimate | Std. Error | t value | Pr(>\|t\|) | Significance |
|---|---|---|---|---|---|
| (Intercept) | 1.74241 | 0.08597 | 20.267 | < 2e-16 | *** |
| log(basalarea) | 1.37262 | 0.01606 | 85.443 | < 2e-16 | *** |
| log(height) | 0.01387 | 0.01660 | 0.835 | 0.403776 | |
| log(treedensity) | -0.33988 | 0.01569 | -21.669 | < 2e-16 | *** |
| shannon_species | 0.04944 | 0.01308 | 3.781 | 0.000167 | *** |
| shannon_structural | 0.06137 | 0.02273 | 2.700 | 0.007071 | ** |
| Residual standard error | 0.1622 on 914 degrees of freedom | | | | |
| Multiple R-squared | 0.976 | | Adjusted R-squared | 0.9758 | |
| F-statistic | 7423 on 5 and 914 DF | | p-value | < 2.2e-16 | |

Table 7. ANOVA of the final, cleaned model.

| | 2.5% | 97.5% |
|---|---|---|
| Intercept | 1.57368016 | 1.91114212 |
| log(basalarea) | 1.34109210 | 1.40414803 |
| log(height) | -0.01871307 | 0.04644486 |
| log(treedensity) | -0.37066745 | -0.30909951 |
| shannon_species | 0.02377384 | 0.07510166 |
| shannon_structural | 0.01675577 | 0.10599173 |

Table 8. 95% confidence interval of the intercept and predictors.

$$\mathbf{\log(Carbon\_storage) = 1.74241 + 1.37262 \times \log(Basal\_area) + 0.01387 \times \log(Height) - 0.33988 \times \log(Tree\_density) + 0.04944 \times Shannon\_species + 0.06137 \times Shannon\_structural}$$

Equation 6. Multiple regression model with logarithmic transformations showing the relationship between aboveground carbon storage and forest variables. The model explains 97.6% of the variance in carbon storage across oak-pine forests of the southeastern United States ($n = 914$, $p < 0.001$)

**Cross Validation**

The last step was to run a cross validation. A 10-fold cross validation with the caret package was run to evaluate the model's performance. The model achieved a RMSE of 0.16, approximately ±18% error, and a MAE of 0.13, approximately ±14% error, on the log-carbon scale. It explained 97.6% of the variance out-of-sample, closely matching the in-sample $R^2$, indicating minimal overfitting. Overall, these results demonstrate that the model generalized well to new data and had a strong predictive accuracy for log of carbon storage.

**Model Interpretation**

The final model revealed that basal area, as a proxy for stand age, tree density, and species diversity, were highly significant predictors for carbon storage in oak-pine forests. Specifically, the model showed a positive relationshiop between basal area and carbon storage, suggesting that older stands with larger trees are more effective at storing carbon, which makes sense logically too. Conversely, tree density showed a negative relationship with carbon storage, suggesting that higher tree densities may limit carbon storage, possibly due to higher competition for resources or less light penetration. The species diversity and strucutral diversity coefficients were significant and positive, but did not seem to be as important as previous literature has indicated they are. The height variable was also not significant after transformation, indicating that it did not contribute strongly to carbon storage in this model.

**Discussion**

The results of this study have similarities and differences with previous research on forest carbon storage. Fatunsin and Naka (2025) emphasized the important role of structural diversity in enhancing carbon storage; however, this study found that it was not as impactful as anticipated. In contrast, Crockett et al. (2023) found that structural diversity significantly affects carbon storage due to varied canopy structures. The model generated in this study supports this finding, but only basal area was a really dominant factor. The study by Ullah et al. (2023) also highlighted tree diversity as a significant contributor to carbon storage, which was consistent with the positive coefficient found in this model. The negative relationship observed with tree density is also worth noting, as it suggests that there could be different interactions between climate and tree characteristics in oak-pine forests compared to the other studies analyzed in this paper.

**Implications for Further Research**

This study was extremely valuable in understanding which factors affect carbon storage in the mixed oak-pine forests of the southeastern U.S. However, further research must be done to fully understand the role of structural diversity in these forests, especially because of the contrast of previous research and the findings in this study. Future studies could explore functional divergence and how specific traits such as tree crown shape or branching patterns could affect carbon sequestration in these ecosystems. Additionally, expanding the scope of the study to include other stand age variables could provide more detailed information on how temporal variables affect carbon storage besides just basal area. Understanding interaction effects in a future model, especially between climate factors like temperature and precipitation, could also help provide further understanding on how carbon storage can be increased. Finally, similar to Ullah et al. (2024), examining the relationship between understory and overstory carbon storage could provide more insight.

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