A Comparison of Aboveground Biomass in Mature Old-Field Forests and Hardwood Forests of the Piedmont Using High Resolution LiDAR Data

By

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Executive Summary

In the face of climate change, policy makers are increasingly interested in utilizing forests for their ability to sequester carbon. Retaining carbon in forests is the objective of various programs that aim to combat climate change. With the growing role of forests in a mitigation strategy, and in order to create effective policies, there is much need for research and two of these research areas are explored in this study.

First, as programs such as REDD+ provide suggestions on forest management strategies, it is necessary to have an understanding of different forest ecosystems within a landscape. A variety of forest ecosystems demands a variety of forest management practices, assigned according to each forest's needs and what it has to offer. There are two common forest ecosystems within the southern Piedmont. Mature old-field forests established themselves on agricultural fields that were abandoned in the mid-1900s. These forests are about 65 to 85 years in age today and consist primarily of pine species. Another, less common forest type of the southern Piedmont are hardwood forests which are old oak-hickory forests that were never cultivated. These two forest types represent different stages of ecological succession and this study is interested in how much AGB is contained within these two forests.

- **Research Question 1:** Is there a difference in biomass between hardwood forests and mature old-field forests?

Second, with rising interest in carbon accounting as a mitigation strategy, there is a need for an efficient and consistent method of biomass quantification. Therefore, this study aims to explore Light Detection and Ranging (LiDAR), a still somewhat novel technology, for its the ability to predict biomass. Airborne scanning LiDAR is a promising technique for efficient and accurate forest volume and biomass mapping due to its capacity for direct measurement of the three-dimensional vegetation structure.

- **Research Question 2:** How well can LiDAR predict biomass?

In this study discrete return, high-resolution LiDAR data was collected over a 150 km^2 site in Sumter National Forest of western South Carolina. The LiDAR data was used to compare aboveground biomass of mature old-field forests and neighboring hardwood stands. Metrics were derived from the LiDAR data and a step-wise multiple linear regression was calibrated with field measurements (R2 =0.722,

$F_{2,32} = 45.23$, $p < 0.001$). The resulting equation below predicted biomass from three LiDAR derived variables:

Biomass (Mg/ha) = $9.88089279 - 4.87146480 * \mathrm{Log10}(101 - X_1) + 0.05747143 * X_2 X_3$

X_1 = Percent Canopy Cover

X_2 = Mean height

X_3 = Standard Deviation of heights

This biomass model was then used to predict the distribution of AGB across the study site. A one-tailed paired t-test indicated that mean AGB was significantly higher in hardwood sites (188.6 ∓ 26 Mg ha^{-1}) than in mature old-field forests (143.3 ∓ 22 Mg ha^{-1}) ($t = 5.22$, $df = 21$, $p < 0.001$).

The results of this study have implications for climate change policy. If forests of the Piedmont are to be conserved and protected from development or agriculture, it would be best to protect hardwood forests. These forests contain more carbon, and therefore removing them would result in a greater release of CO_2 into the atmosphere in comparison with mature old-field pine forests. However, secondary pine forests may also be managed for climate change mitigation. Though they may contain less carbon than hardwood stands, the high productivity of these pine stands, especially when they are young, results in rapid removal of CO_2 from the atmosphere.

Finally, the ease and consistency with which LiDAR was used to quantify biomass across the landscape suggests that it would be a great tool for carbon accounting. Despite the variety of forest types (pine and hardwood, young and old) within the study site, a single model was able to explain 72% of the variation in biomass across these different sites. If it can be done affordably, this study supports the use of LiDAR for monitoring biomass contained in the forests of countries participating in cap-and-trade programs.

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Introduction

Within the last decade, concern about the effects of climate change has heightened the interest in global forest volume and biomass stocks. As many human activities pump CO_2 and other greenhouse gases into the air, forests reverse the effects. Trees remove CO_2 from the air through photosynthesis and sequester it in their biomass -- biomass is composed of about 50 percent carbon. Forests act as carbon sinks at a time when CO_2 needs to be removed from the atmosphere as quickly as possible. Therefore, retaining carbon in forests is a climate change mitigation strategy used by policy makers.

For example, the United Nations program, Reducing Emissions from Deforestation and Forest Degradation in Developing Countries (REDD+), provides incentives for developing countries to conserve their forests. These tropical countries in particular experience the highest levels of forest conversion, primarily to agriculture. Such deforestation contributes to 10% of global greenhouse gas emissions (The REDD Desk, 2015). Therefore, REDD+ provides financial incentives that encourage land owners to retain forests rather than converting them for other lucrative uses. Not only does REDD+ promote a decrease in CO_2 emissions to the atmosphere, it also provides incentives to enhance the removal of CO_2 through a variety of forest management strategies (Parker et al., 2009).

REDD+ aims to . . .

"(a) Reduce emissions from deforestation

(b) Reduce emissions from forest degradation

(c) Conserve forest carbon stocks

(d) Encourage sustainable management of forests

(e) Enhance forest carbon stocks"

- (The REDD Desk, 2015)

Developed nations are also turning to wood as strategy for fighting climate change, though in a different way. These countries have been weening themselves from coal and oil and replacing these energy sources with renewable resources including wind, solar and biomass. Biomass energy, such as wood, is said to be carbon neutral because forests cleared for wood pellets can be replanted. The technological advancement of power plants in recent years also means that burning wood can be cleaner, by minimizing the emission of pollutants and fine particulates.

The European Union (EU) has become the largest global consumer of wood as it attempts to reach renewable energy goals. In 2008, the EU launched a policy initiative that included a target to increase the use of renewable resources by 20 percent by the year 2020. According to EUROSTAT (2014), renewable energy consumption in the EU nearly doubled between 2002 and 2012. By 2012 wood provided 47 percent of the renewable energy for the EU and 5.1 percent of the total energy consumed. However, most EU Member States are unable to produce enough wood to satisfy their consumption. Therefore, the EU; especially the UK, Belgium and the Netherlands; imports much of its wood. It imported 7 million tons in 2013 (EUROSTAT, 2014) and most of the imported wood comes from Canada and the U.S.

The U.S. provides about 45% of the wood pellets for the EU (Galik & Abt, 2015). Most of this wood is sourced in the southeast, due to the productivity of intensively managed plantations (Jonker et al., 2014) but also thanks to a well-established logging industry, a slowly declining paper and pulp industry, and access to waterways and ports, enabling relatively easy international transport (Goh et al., 2013).

In light of the imminent risks of climate change and the growing interest in forests as a solution, policymakers and scientists are interested in the distribution of forests across the landscape. Where is biomass highest? Which forests sequester the most carbon? How much CO_2 will be released should a forest be cut and burned? In order to answer these questions, we must be able to quantify the biomass held within forests. While spectral and radar remote sensing data has been used to estimate forest volume and aboveground biomass (AGB), it is thought that Light Detection and Ranging (LiDAR) data can predict these metrics more accurately due to its ability to detect the three-dimensional shape of a stand (Zhao et al., 2012). LiDAR offers an efficient and consistent method of estimating biomass for large sites.

LiDAR data are collected from airplanes that emit pulses of light at a forest canopy below. The pulses hit objects such as trees and shrubs, and then bounce back to the plane's sensor, which then records the elevation and the geographic coordinates of the object. The result is a cloud of points that give an indication of the forest's three dimensional structure (figure 1). Research has demonstrated that LiDAR measured heights are highly correlated with volume and biomass (Lefsky et al., 1999; Means et al., 1999). Because of the biophysical properties of trees, stem diameter

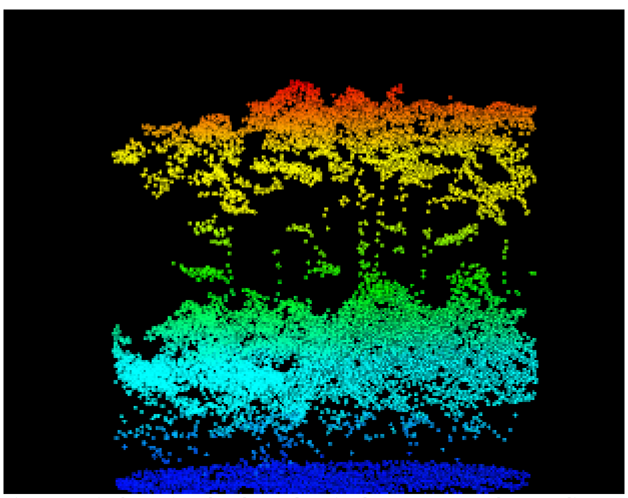

Figure 1: LiDAR point cloud. Each point has an x,y, and z coordinate associated with it. Points are colored by elevation. The tree canopies are red and the bare earth is dark blue.

typically increases as trees become taller, further increasing wood volume and mass.

Study Objectives

As the EU turns to southeastern forests to reach their renewable energy goals and as the world combats climate change, it is important to understand which forests are better suited for energy production and which may be better suited for other forest management options such as conservation. This requires an understanding of the distribution of biomass within these forests. This study looks particularly at two common forests ecosystems of the southern Piedmont: mature old-field pine forests and uneven-aged hardwood forests.

The southern Piedmont was heavily farmed for about 150 years from the early 1800s to the mid-1900s. Farmers grew corn, wheat, but especially cotton. But by the 1920s, they began to abandon their land because it was so eroded and exhausted that it could no longer support crops. Farmers moved away for better land and for jobs in the cities (Richter et al., 2014). Today, mature old-field pine forests stand on many of those old agricultural fields. These forests consist mostly of pine (lobllolly (*Pinus taeda*) and shortleaf (*Pinus echinata)* in particular) because pine species are early successional, fast growing species and can tolerate sandy, low nutrient soils. These old-field forests are 65-85 years old and make up a majority of Piedmont forests today.

Another, less common forest type in the Piedmont are hardwood forests dominated by oak and hickory. These small patches of forest escaped cultivation. However, they are far from pristine condition. Their fire regimes have been altered and they have been grazed and harvested in the past.

These two forests ecosystems represent different stages of forest succession. Forest succession describes the changes in a forest after a disturbance (figure 2). In the case of old-field forests, the disturbance was agriculture. Once the fields were abandoned, grasses colonized the bare soil, then shrubs moved in and then pines. Over 65 years after field abandonment, the pine trees are mature and there are likely shade-tolerant hardwoods growing into the understory. Eventually these hardwoods will replace the pines in the canopy and transition to oak-hickory forests that resemble our hardwood stands. Biomass changes with each stage of forest succession. It is low at first, increases rapidly with young pine growth, and plateaus in oak-hickory forests.

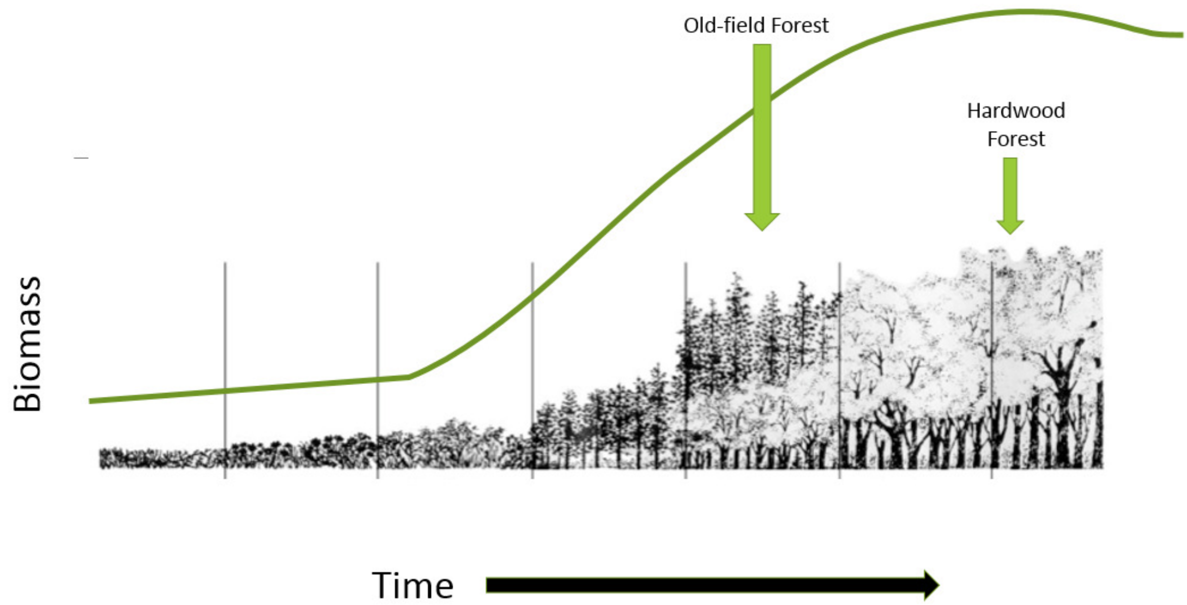

Figure 2: Mature old-field forests and hardwood forests represent different stages of forest succession. Biomass changes with each stage of succession (Adapted from: (Duke Forest, n.d.).

In this study we are interested in comparing the current state of biomass between mature old-field forests and hardwood forests of the Piedmont. Have mature old-field forests caught up to hardwood forests in terms of biomass? We hypothesize that hardwood forests will contain significantly more biomass than old-field forests. Though the pines may be mature and fully grown, hardwoods tend to be denser than softwoods and higher density results in higher biomass.

> **Research Questions:**
>
> 1) Is there a difference in biomass between hardwoods and mature old-field forests?
> 2) How well can LiDAR predict biomass?

This study is also interested in exploring LiDAR's ability to predict biomass. Although there are studies that have successfully used LiDAR to estimate biomass, it is still a novel technology that requires exploring and further study. For example, though LiDAR may be useful in one landscape, it may not be so useful in another. There are also many different ways in which scientists have processed and used LiDAR and this study will explore some of those methods.

This study will 1) use LiDAR data to calculate plot level metrics 2) regress LiDAR based metrics with field based biomass estimates to create an AGB model for the site 3) use the model to predict biomass across the landscape and 3) statistically compare the biomass levels of hardwood sites and old-field pine sites.

Study Area

This study is located within the Calhoun Experimental Forest within the Enoree Ranger District of Sumter National Forest in western South Carolina. The closest town is Union, SC and Spartanburg, SC is about 40 km to the northwest (figure 3). The Calhoun Experimental Forest is 2,078 acres and was established in 1947 under the direction of Louis Metz. Today the forest experiments are managed by Duke University and the U.S. Forest Service Southern Research Station.

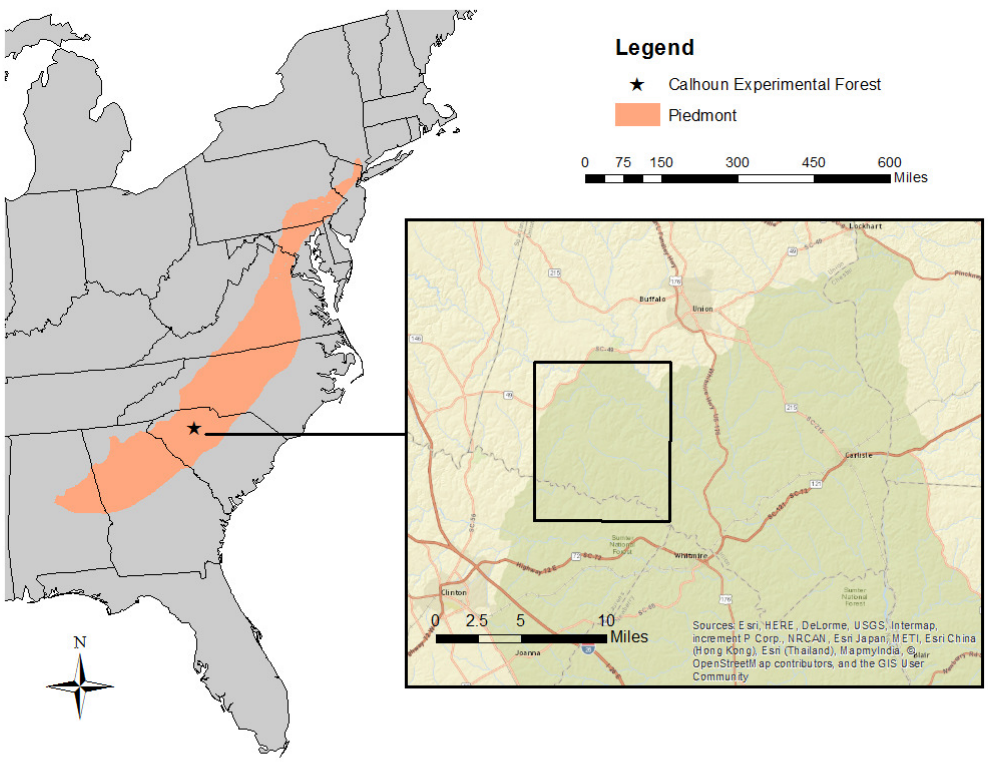

Figure 3: The study site within Calhoun Experimental Forest, in the southern Piedmont.

The soils here are old, well weathered Ultisols derived from granitic-gneiss. The topsoil, where not eroded, is course grained while subsoils are rich in kaolinitic clay. These soils are low activity and therefore exhibit low nutrient retention. The climate is warm and humid with average an precipitation of

1,215 mm and an average temperature of 17 °C (Li & Richter, 2012). Most of the forests on this site are old-field pine while hardwoods make up less than 1% of the study site.

This land was heavily farmed for corn, wheat and particularly cotton during the 1800s and early 1900s. The Calhoun Experimental Forest demonstrated "the poorest of Piedmont conditions" (Metz, 1958) due to the extent and severity of the eroded and gullied landscape.

Methods

Data

The LiDAR data were collected over 150 km^2 (58 mi^2) and were discrete, multiple return (up to 4 returns per pulse), high resolution data with a pulse density of about 9 pulses/ m^2. They were collected in July and August, 2014, during leaf-on conditions, allowing retrieval of canopy metrics.

The vegetative plot data were collected from 35, 15 meter radius (0.07 ha) plots and collected in July and August, 2014. Within each field plot, species, diameter at breast height (DBH), and the height of all trees above 6" DBH were collected. Smaller stems are minor components of stand biomass in mature forests and therefore were not included in this analysis.

Field plots were located in secondary pine stands of various ages, and in hardwood stands. The geographic coordinates of plot centers were recorded with Trimble GeoXH™ handheld GPS with sub-meter horizontal accuracy. It is important to have a very accurate GPS device when determining the plot locations to ensure that the field plots corresponds with the LiDAR data clipped to those locations.

Field data processing

The biomass held within each tree was calculated using allometric equations and then total biomass was summed for each field plot. Zhao et al. (2012) found that allometric equation choice can impact the ability of LiDAR data to estimate AGB. Although they are more computationally intensive, Forest Inventory Analysis (FIA) equations were used in this study because they have demonstrated significantly higher correlations with LiDAR derived metrics than national Jenkins equations. This is because FIA allometries include a term for tree height whereas Jenkins allometries require DBH alone. LiDAR records height, therefore LiDAR metrics are more highly correlated with height rather than DBH (Duncanson et al., 2015; Zhao et al., 2012). Moreover, FIA equations appear to be more accurate than those of Jenkins ((Zhao et al., 2012). Although there are separate Jenkins equations for softwoods and hardwoods, biomass estimates based on FIA allometries are species specific, thus taking into account tree density. FIA also has separate equations for different components of the tree, such as the stump, branches, wood, and bark (Zhao et al., 2012).

LiDAR data processing

FUSION software was used to process the LiDAR data. There are several advantages to using FUSION over other software. FUSION is free, and because it was developed by the forest service it is very good for forestry applications. FUSION has a series of tools that allow easy calculation of forest statistics at the plot level (Behrendt & Mitchell, 2013).

First, a digital terrain model (DTM) was created from bare earth returns. Then the LiDAR data was clipped to the exact locations of the field plots and the height value of each point was normalized by subtracting the corresponding DTM elevation value. A series of statistics describing the distribution of points within each plot was then calculated.

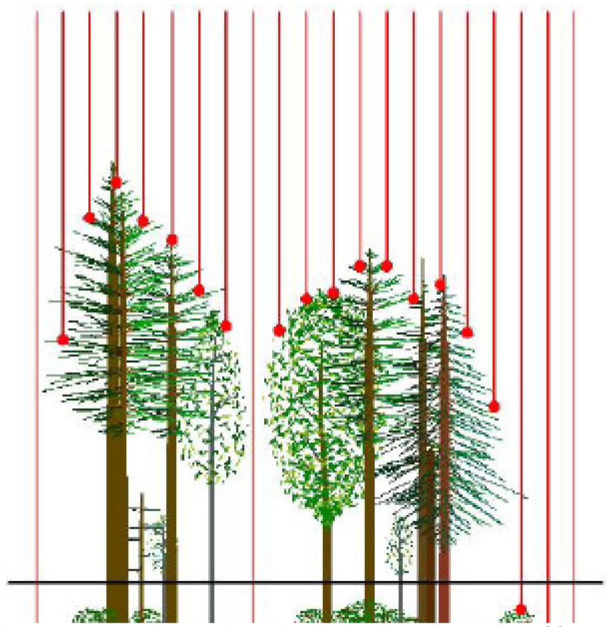

Figure 4: Percent Canopy Cover is calculated as (the number of first returns above 10m) / (total number of first returns). Source: (McGaughey, 2014)

Among these plot-aggregated metrics was a calculation of percent canopy cover. Percent canopy cover is calculated as: (the number of first returns above a height break) / (total number of first returns) (figure 4). The user is therefore required to enter a height break value that should represent where the shrub layer ends and the canopy begins. Most shrubs would have been excluded from the field data collection because the DBH cut-off was at 6 inches DBH. Therefore, shrubs should also be excluded from this LiDAR metric so that it does not include information that is not contained in the field data (which would impact the ability for this metric to explain some of the variation in observed biomass). Histograms of the distribution of heights within the point cloud of each plot was used to estimate the height break. Separate peaks in the histogram indicated shrub and canopy strata. The right tail of the lower peak was used to determine at what height the shrub strata tapered out. This threshold was compared between plots and averaged 10m.

Calibrating the biomass model

Next, in order for the LiDAR data to be able to predict biomass anywhere on the landscape, it needed to be calibrated with the field biomass observations. This was done by running a step-wise multiple linear regression in which the LiDAR derived metrics were used to predict observed biomass estimates. This regression was conducted with the R-statistical package (R Core Team, 2013). Variables were removed to resolve multicollinearity. Then backward model selection was used to remove insignificant variables and to identify the most parsimonious model.

Landscape scale biomass distribution

Finally, we were interested in examining the distribution of AGB across the landscape. First statistics were calculated for each pixel within the study area using FUSION. Then in ArcMap 10.2 (ESRI, 2013) the biomass model was applied to each pixel to create a landscape scale biomass raster. A pixel size of 27m x 27m was used because this was similar to the area of the field plots used to calibrate the data. Non-forested areas were masked out of this raster so that the model was not applied inappropriately. Pixels falling below the minimum (minimum values were rounded down and a slight buffer was subtracted from these values to create a generous threshold) of the plot based LiDAR metrics used to calibrate the model were deemed "non-forest". This included any pixels falling below the following thresholds:

- Mean Height: 7 meters
- Standard deviation of heights: 2
- Percent Canopy Cover: 30%

Comparing old-field and hardwood forests

Forest type is not the only factor affecting forest biomass, therefore other variables that also influence these values had to be controlled for. This was accomplished by pairing old-field plots with hardwood plots in similar environmental settings, using the biomass model to estimate biomass within these plots and then statistically comparing biomass using a paired t-test.

When pairing the plots, one plot in each pair was to be located in a hardwood stand and the other in a mature old-field stand. Hardwood stands were located first because these ecosystems are scarce in comparison (less than 1% of the site). Slope maps were used to help locate these stands because slopes on these unplowed soils rarely rise over 20 percent. A 1933 areal image also aided the identification of these forests by indicating where there were intact, closed-canopy forest patches when the rest of the land was in agriculture. Additionally, site visits were made to examine the geology, soils and trees to verify that these sites were indeed uncultivated hardwood stand.

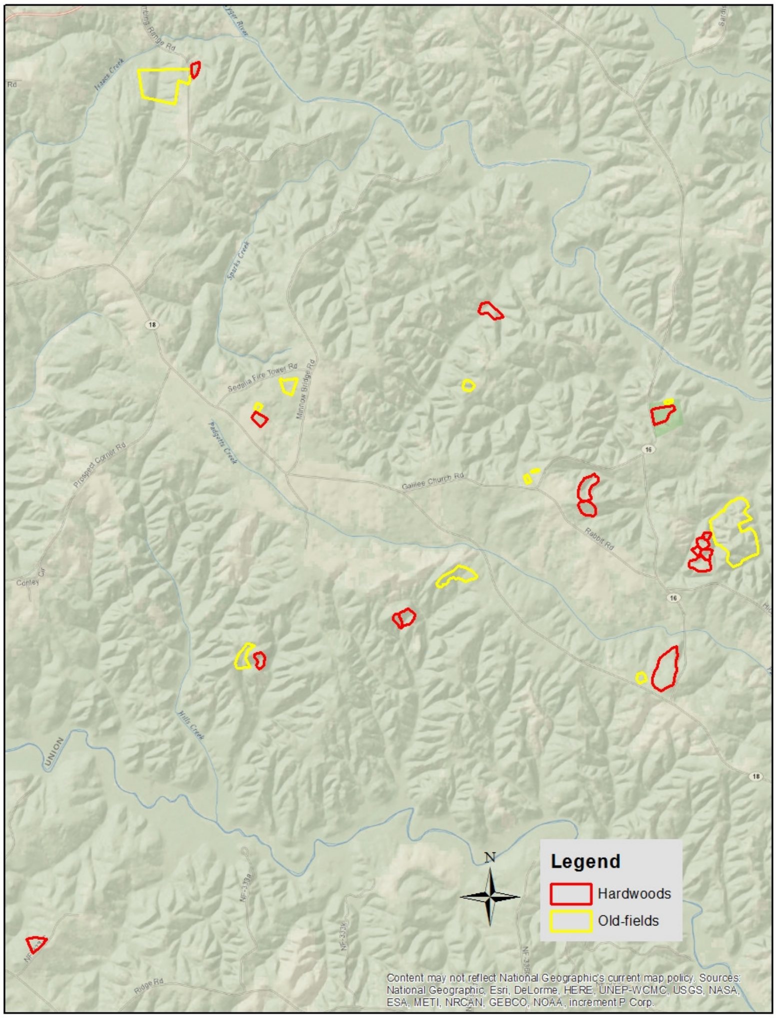

Figure 5: Old-field and hardwood forests sites.

Then mature old-field forests were selected and paired with hardwood sites based on proximity (figure 5). This was to ensure that paired forest plots grew on soils composed of similar geologic substrates. Then, within these paired stands, the paired plots were located, one plot in the hardwood site and one within the old-field. To ensure similar moisture and light regimes, the location of these plots were paired based on aspect, slope, and topographic position index (TPI) (figures 6 and 7).   Slope and aspect are known to impact tree diameter, and thus biomass (Saremi et al., 2014). Slope, aspect and TPI were calculated in ArcMap 10.2 (ESRI, 2013) from a digital elevation model (DEM), and then averaged for each plot. Aspect was less important when pairing plots of low slope.

Topographic Position Index (TPI) identifies ridges, slopes and valleys within a landscape. It is determined by comparing the elevation of a cell with the mean elevation of neighboring cells (Weiss, 2001). It is therefore scale dependent: a smaller neighborhood reveals smaller features in the landscape. Fine (50-80m annulus) and course (100-150m annulus) scale TPI rasters were used to pair the plots. These neighborhood sizes were based on the relatively low relief of the Piedmont. Within the study area, the elevation range is on the order of 100 meters.

A total of 22 pairs were selected and were located across the spectrum of TPI values, to ensure that biomass values would be compared on a variety of landscape features. The LiDAR point cloud was clipped to these 44 plot locations and the biomass model was used to estimate biomass at these locations. A one-tailed (because the hypothesis was that hardwoods would contain more biomass) paired t-test was then used to statistically compare biomass between the two forest ecosystems using the R-statistical package (R Core Team, 2013).

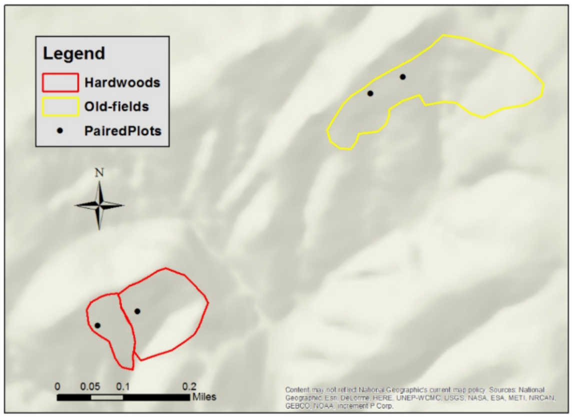

Figure 6: Two plots from the hardwood stand (red) were paired with the two plots in the mature old-field stand (yellow).

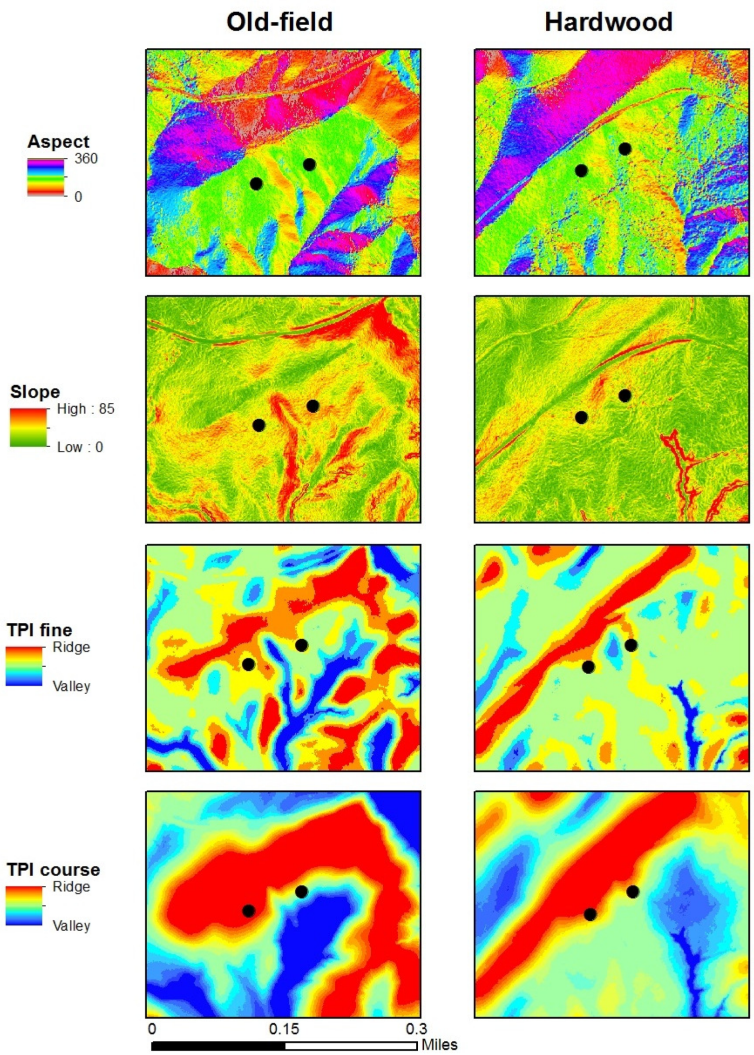

Figure 7: The two hardwood plots and the two old-field plots in figure 6 were paired based on three environmental factors: aspect, slope (degrees), and TPI (fine and course scale). By comparing these datasets side by side, it is possible to see that the pairs were made because of congruent environmental settings.

Results

Final Model

Equation 1 shows the final result of the multiple linear regression. After removing non-significant variables, percent canopy cover, mean height and the standard deviation of heights were the remaining variables included in the model, and each of these variables was significant ($p<0.001$). These three metrics provide different, non-redundant information about forest structure and therefore it was logical that they would complement each other. Percent canopy cover was negatively skewed, therefore a Log10(K-X) transformation was necessary to fulfill assumptions of normality. This significantly improved the fit of the model.

Equation 1: Model predicting biomass from LiDAR derived metrics.

$$\text{Biomass (Mg/ha)} = 9.88 - 4.87 * \text{Log10}(101 - X_1) + 0.0575 * X_2 X_3$$

X_1 = Percent Canopy Cover
X_2 = Mean Height (m)
X_3 = Standard Deviation of Heights

The resulting model explained 74% of the variation in observed biomass values ($R^2 = 0.74$) and the model was significant ($p<0.001$). Model diagnostics indicated that residuals were normally distributed and randomly scattered (figure 8). Cooks distance showed that one plot carried some leverage. So the model was tested without the high-leverage plot to ensure that without it, the model would still fit. Model fit improved with its removal ($R^2=0.76$), so the model was retained. A graph of observed versus predicted AGB values showed points hugging the 1:1 line, indicating that the model was able to predict values similar to those that were estimated for the field plots (figure 9).

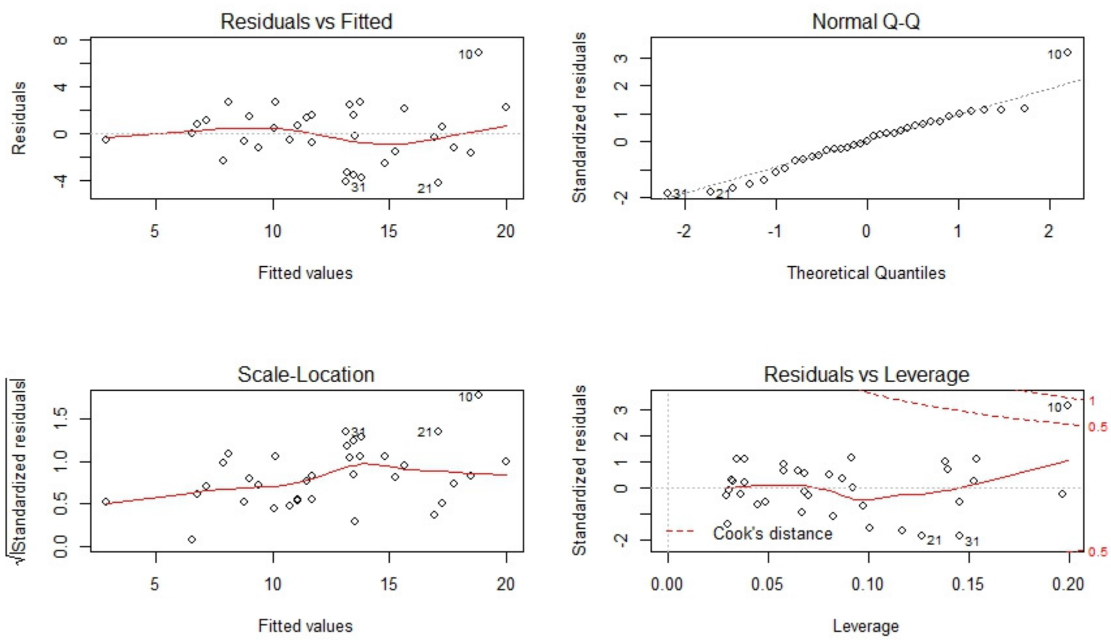

Figure 8: Diagnostic plots for testing model fit. (Top left) In the first plot of residuals, points are randomly scattered around the centerline indicating no violation of homoscedasticity. (Top right) The second plot is a q-q plot. There are no significant departures from the line, indicating that residuals are normally distributed. (Bottom left) The third plot of standardized residuals versus the fitted values shows an even scatter of points around the line, indicating no problem of homoscedasticity. (Bottom right) The final plot shows cooks distance for each observed value. This plot indicates that point #10 carries a lot of leverage. Model fit improved when this point was removed.

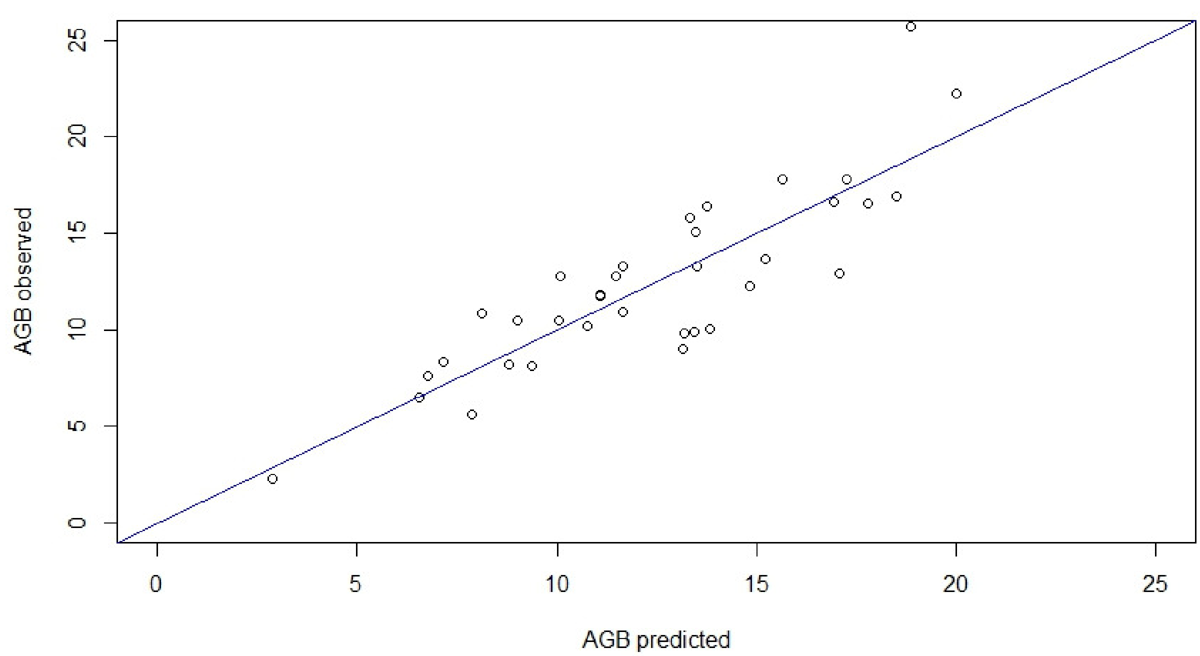

Figure 9: A graph of observed AGB values vs. AGB predicted by the model. If the points were to fall exactly along the blue line, there would be a 1:1 relationship. The tight scatter of points along this line indicates that the values are similar.

Biomass across the landscape

The model was applied to the entire site area (figure 10). Extrapolated values outside of the range (33-364 Mg/ha) of the observed biomass values used to calibrate the model were identified (figure 11). Extrapolation occurs because it is nearly impossible to sample the full range of variability across the landscape. Extrapolating values can result in prediction errors, therefore it is good to be aware of the model limitations and how much of the landscape falls outside of this range. However, we can see from the figure that very little of the landscape fell outside of this range.

We can see from figures 10 and 11 that floodplains appear to have especially high biomass. To examine this pattern, pixels containing above average biomass were selected and overlaid on a TPI raster (figure 12). The map shows these pixels do in fact appear to fall within flood plains. Therefore, it was very important that TPI was controlled for when pairing hardwood and old-field forest plots.

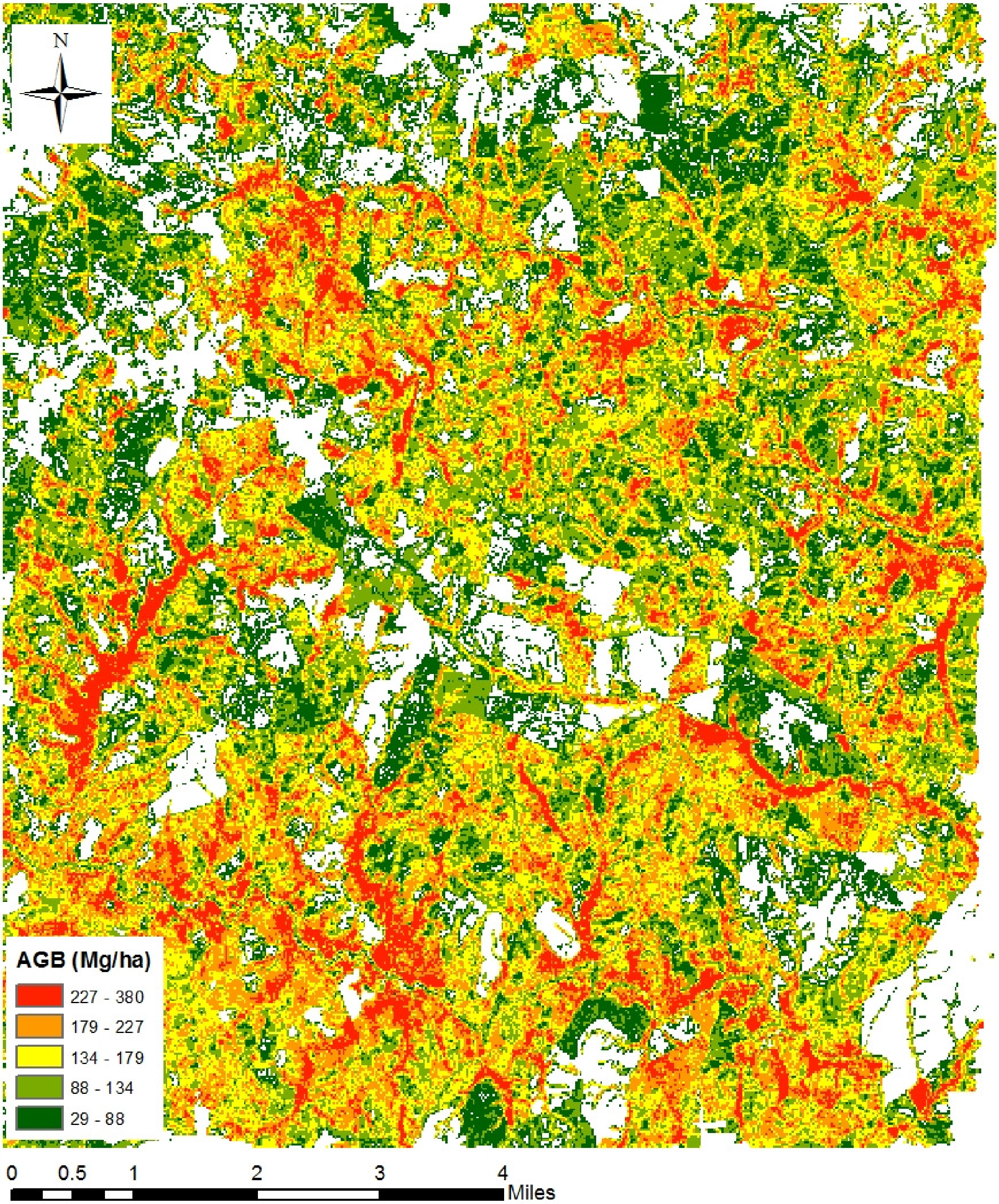

Figure 10: Distribution of aboveground biomass across the study site.

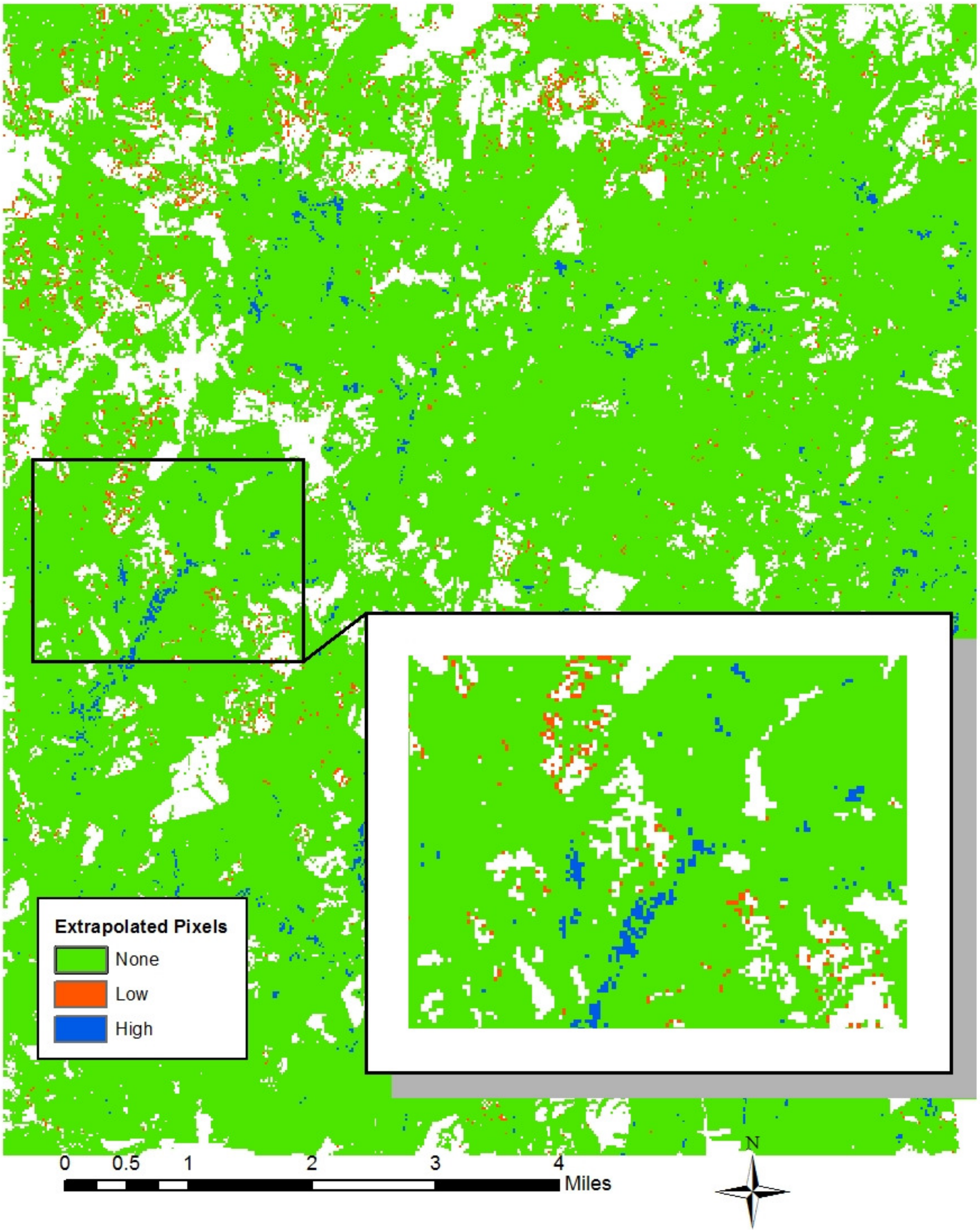

Figure 11: Extrapolated AGB values outside of the range of the data used to calibrate the model.

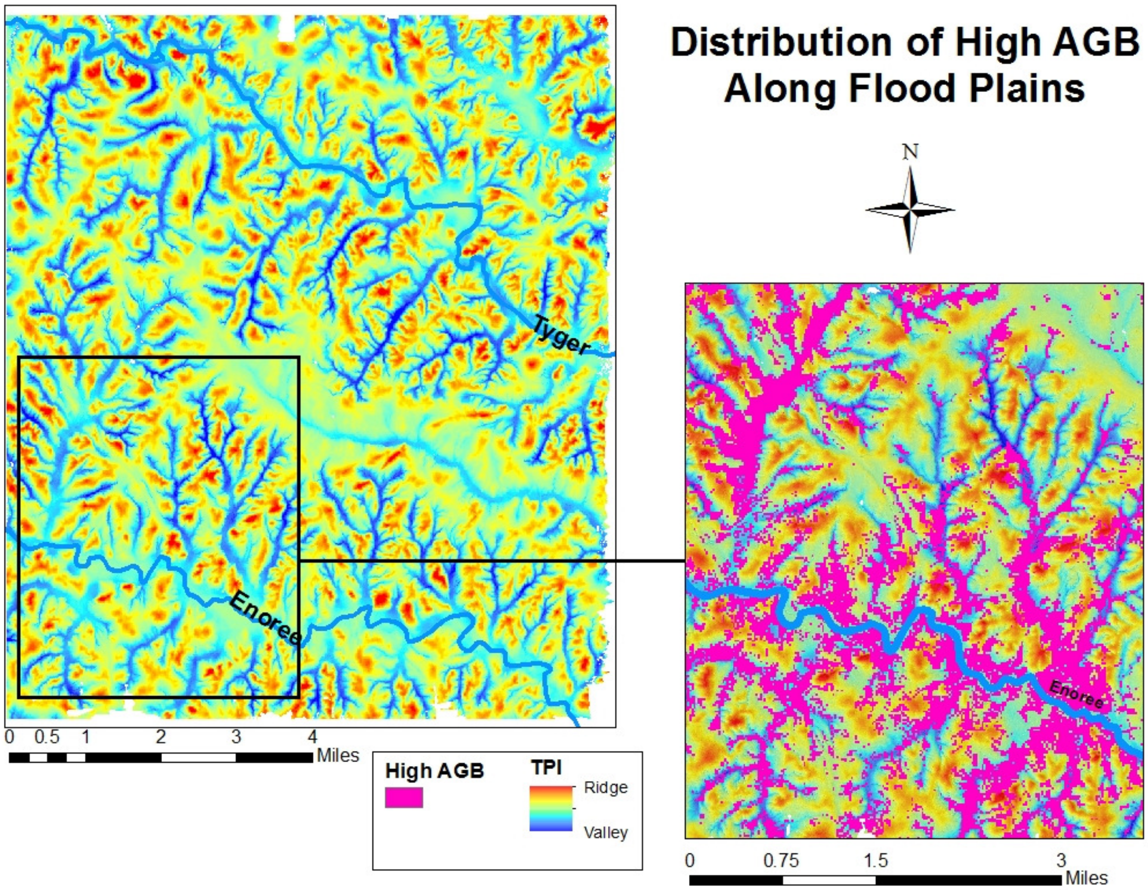

Figure 12: Distribution of high AGB along flood plains

Comparison of forests

The results of the one-tailed paired t-test indicated that hardwood forests contained an average of 45.2 Mg/ha more than mature old-field forests ($p<0.001$). However, there is always the possibility that a difference between populations will be found when there is none (type I error). Therefore a power analysis was run to test the strength of the t-test and its ability to detect a statistically significant difference when the null hypothesis is in fact false. The power analysis indicated that the t-test was 98% likely to have correctly rejected the null hypothesis. Mature old-field stands averaged 188.6 Mg/ha and hardwood stands averaged 143.3 Mg/ha (figure 13)

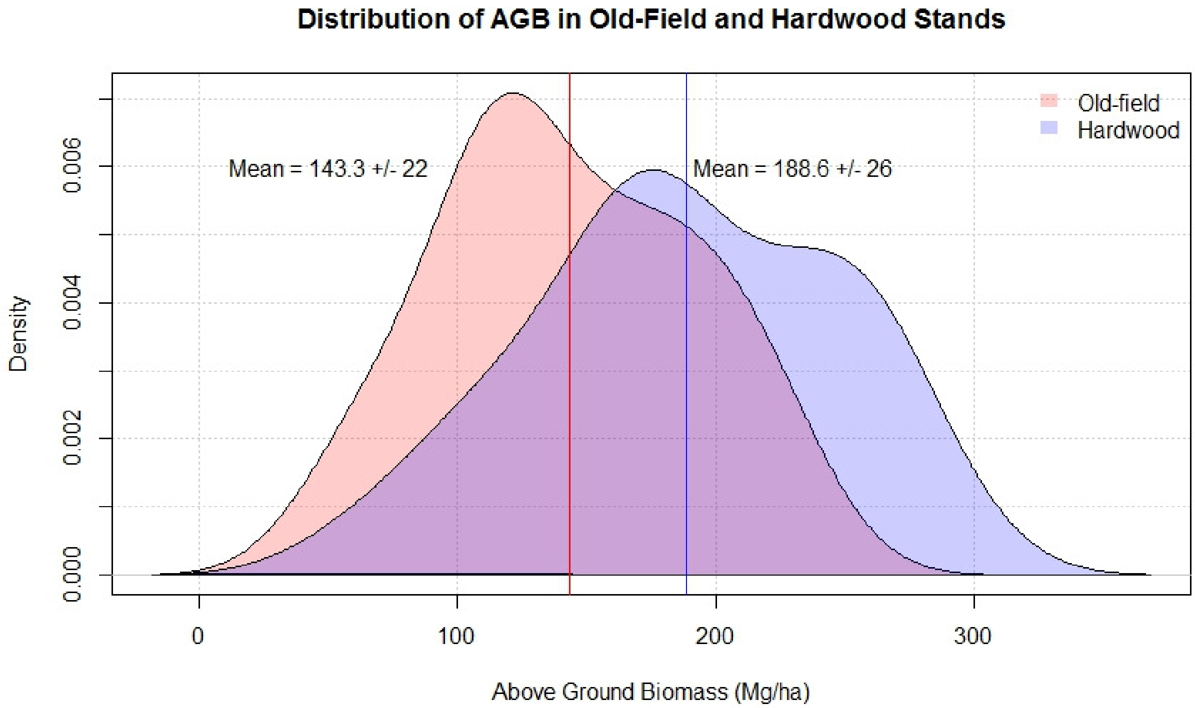

Figure 13: Distribution of AGB in old-field and hardwood forests and 95% confidence interval of means.

Discussion

This study found that mature old-field forests, about 70 years old, have not yet caught up with hardwood stands in terms of biomass. They are at different stages of succession and it may take a complete transition to hardwoods before they reach a similar state. However, because of the history of intense land use at these sites, it may be that once they have transitioned to an oak-hickory forest they still will not carry the same amount of biomass. It would require another study to look at whether the impaired soils affect biomass, because the forests must be compared at the same stage in succession.

This study also has implications for climate change policy. One climate change mitigation strategy is to protect forests from deforestation. If forests of the Piedmont are to be protected from development, agriculture or other forms of conversion, it would be best to protect old hardwood forests because they contain more carbon, and because removing them would result in a greater release of CO_2 into the atmosphere in comparison with younger pine forests.

It would also be practical to protect these forests from wood pellet production. Though, they would provide more energy, these forests would not provide a carbon neutral option. Once the forests were cleared and used for energy, the pine forests that would take their place wouldn't replace the carbon that was removed for a very long time, perhaps centuries. Young pine, on the other hand, is carbon neutral, because the carbon can be reabsorbed at a much faster rate.

Though they may contain less carbon than hardwood stands, the high productivity of pine stands can also be used to combat climate change. Removal of CO_2 from the atmosphere is more rapid in these young, fast growing stands. Thus, managing forests for young pine can enhance removal of greenhouse gases. This includes planting pines and improving the productivity of degraded forests.

Finally, this study also contributes to the body of literature that has discovered the usefulness of LiDAR for quantifying biomass. Despite the variety of forest types (pine and hardwood, young and old) within the study site, a single model was able to explain 74 percent of the variation in the biomass values across these different sites. The ease and consistency with which LiDAR can be used to estimate biomass across large areas of land suggests that it would be a great tool for carbon accounting. If it can be done affordably, this study supports the use of LiDAR for monitoring biomass in the forests of countries participating in REDD+. However, LiDAR only provides information on the physical structure of the forest, not densities of the trees, and is therefore limited in its ability to estimate biomass in forests with a large variety of species and thus a wide range of densities (Duncanson et al., 2015) . Biomass estimation could be improved if hyperspectral data were used to identify individual tree species or if separate models were created for softwood and hardwoods.

Conclusion

Conversion of forests to other land uses results in CO_2 emissions. The ability to quantify biomass within forests allows us to select forests for conversion that will result in lower emissions. In the Piedmont, pine forests are the preferable alternative to hardwood forests for conversion, because they contain less biomass, thus emitting fewer greenhouse emissions. A similar biomass comparison between forest types in the tropics is something REDD+ could benefit from. The results of this study are not transferable to other parts of the world because the species that characterize different stages of succession vary across ecosystems. It may be, for example, that old-growth forests of certain tropical ecosystems have lower density wood than their old-field forest counterparts.

Biomass distribution and the anthropogenic and environmental variables that affect its distribution are important to understand in an age where forest management is increasingly incorporated into policies. While in this study the effect of age on a forest was examined, other factors that should be looked at for their effects on biomass including land use history and environmental variables such as topographic position on the landscape.

Developments in LiDAR technology in recent years have made it possible to analyze an entire landscape efficiently and consistently. More studies should take advantage of this technology and refine the methodologies for LiDAR processing in order to encourage the inclusion of LiDAR into biomass monitoring and verification processes that are necessary for the success of programs such as REDD+.

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