THE IMPACT OF REFORESTATION ON THE CLIMATE OF THE SOUTHEAST

by

Adam Terando

A thesis submitted to the Faculty of the University of Delaware in partial fulfillment of the requirements for the degree of Master of Science in Geography

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by

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ABSTRACT

Human modification of the landscape can potentially have an impact on weather and climate. Numerous climate modeling studies indicate that deforestation or reforestation will have an impact on the climate. Yet, there is much less research that utilizes the climate record to confirm these findings.

This study determined the impact of reforestation on the summer climate of the southeastern United States. Counties in the piedmont area of North Carolina, South Carolina, Georgia, and Alabama were grouped by amounts of forest cover during the period 1948-2001. Three levels of forest cover were compared using an air mass analysis: low, medium, and high forest cover. In addition, county groups with low levels and high levels of forest cover were tested for meaningful differences between temperature, precipitation, and soil moisture.

The air mass analysis showed no consistent trends or differences in the climate attributed to forest cover. The additional analysis showed that when county groups with high levels of forest cover were compared to county groups with low levels of forest cover, there were no differences in the probability of precipitation or the distribution of precipitation events. Forest cover was also found to have no effect on precipitation when daily soil moisture estimates were stratified according to the degree and duration of moisture deficit periods (i.e. drought). Areas with high amounts of forest cover had larger diurnal temperature ranges (~0.3 ^{o}C) but lower daily variability of temperature range than areas with low amounts of forest cover.

Removal of cloud cover to isolate periods of maximum energy exchange between the land surface and the atmosphere confirmed that areas with high amounts of forest cover had higher diurnal temperature ranges but showed decreasing differences between the two groups as soil moisture approached saturation. The temperature results are in agreement with climate models but the precipitation results contradict models predicting decreases in precipitation due to deforestation. These results verify those aspects of the land surface's affect on climate that are well modeled but also point to model areas that are not well constrained and require further work. There is clearly the need for further development of land-atmosphere climate models and for further study of the climate record to understand how land surface alteration affects climate.

Chapter 1

INTRODUCTION

Humans intuitively feel that what grows or is constructed at ground level can have an impact on their weather and climate. A common expression in the United States during the 19th century was, "The rain follows the plow." The expression alludes to the belief that as the American Frontier moved west into the more arid regions of the country, the amount of precipitation would increase once the tough prairie sod was broken open and planted with wheat and corn. This belief was proven wrong as devastating droughts in the 1890s ruined many farm families (Glantz 1994, Bonan 1997). Changing the land from short-grass prairie to wheat or corn did not have a large impact on the amount of precipitation that fell. But the idea that changing a land surface could have impacts on the climate system held.

Today, humans have enormous impacts on the earth's land surface. Cities expand into rural areas, forests are cleared for timber and agriculture, and agricultural areas are abandoned as soils are exhausted and become unprofitable. How do these alterations affect the climate? On the local and micro-scales for example, climate research has quantified the influence of urban buildings, factories, and automobiles in creating an urban heat island (c.f. Oke 1982). Research has also shown that the changes in the sensible and latent heat fluxes caused by neighboring agricultural fields and forests can influence climate on a local scale (Pinty et al. 1989). On the regional scale, Anthes (1983) suggested that long thin bands of vegetation could be used to

enhance convective precipitation in arid and semi-arid regions of sub-Saharan Africa. In addition, the impact of deforestation in the Amazonian Basin on climate has been extensively examined on the local scale (Culf et al. 1995, Lean and Rowntree 1993), the regional scale (Nobre et al. 1991, Sud et al. 1996), and on the global scale (Zhao et al. 2001). Much of this research has also examined the short-term and long-term impacts of this land cover change on climate (Cutrim 1995).

Regional studies outside of the tropics have been somewhat limited and have focused on modeling the climate rather than examining the actual climate record. Notable exceptions are Pielke et al. (1999), who showed that 20th century land surface changes in Florida led to higher temperatures and less precipitation. Bonan (1997) used a general circulation model (GCM) to determine the effects of land cover on climate in the United States over the last 300 years. Gates and Lieβ (2001) also used a GCM to determine the impacts of deforestation and afforestation on Mediterranean climates since Roman times. For such long-term studies, modeling is a necessary approach due to the lack of reliable climate data or detailed land cover data. Nevertheless, most regions of the United States have both climate data and land cover data stretching back at least 50 years.

Both modeling the climate and examining the climate record have shown, for the most part, that land surface changes have a moderate influence on regional and local climates, and little effect on global climate (e.g. Bounoua et al. 2002). But moderate climatic changes can have a large impact on how organisms are able to respond to and adapt to stressful environmental conditions. Research is lacking in determining the existence and magnitude of climatologically-induced stressors on organisms that are caused by land surface changes.

Linking these moderate but possibly crucial climatological changes with their effects is a main goal of synoptic climatology (Sheridan 2000). From insect populations (Muller and Tucker 1986) to asthma admissions in hospitals (Jamason et al. 1996), to heat-stress mortality in humans (Kalkstein and Greene, 1997), synoptic climatology has established relationships between climate and environmental responses to climate. The primary measure of these relationships is through air mass categorization and analysis. Air masses provide a holistic approach to describe meteorological conditions because they are an aggregate of the state of the atmosphere (Sheridan 2000), and it is usually the aggregate of atmospheric components and not individual variables that causes stress on organisms.

Thus, there exists a need to determine the impacts of land surface changes on climate on a regional scale in the mid-latitudes. In the United States, the piedmont and upper coastal plain area of the Southeast experienced extensive reforestation in the 20th century as cotton fields were abandoned due to the combined effects of soil exhaustion, boll weevil infestation, economic depression, and emigration to urban areas. This area has seen rapid population growth around the urban areas of Atlanta, Charlotte, and the piedmont of North Carolina. Consequently, urban heat islands have developed over the new population centers, potentially resulting in more oppressive air masses within these cities that can increase heat-stress and heat related mortality.

Near some of these expanding urban areas, this extensive reforestation may play a role in mitigating the urban heat island effect. The height difference between newly reforested areas and existing agricultural fields increases the surface roughness and forces air parcels to rise. Disparity in the Bowen Ratio between different land surface types can lead to the creation of 'forest-breezes' that cause

mesoscale circulations in the atmosphere. These atmospheric circulations can potentially lead to increased cloud cover and precipitation (Pinty et al. 1989). On the other hand, this reforestation may serve to slightly increase temperatures due to increased stomatal resistance in coniferous trees leading to higher rates of sensible heat flux into the atmosphere. In addition, GCM studies have also shown that the lower summer-time albedo of forests (compared to agricultural areas) will increase air temperature (Gibbard et al. 2005).

This thesis does not attempt to hypothesize that reforestation in the Southeast either enhances or suppresses the effects of oppressive summer air masses. Rather, the hypothesis is that reforestation and forest cover does have an impact on the climate of the Southeast.

Goals and Objectives

While the literature on the impact of land cover on climate is substantial, there is a paucity of research that directly examines the climate record to determine the effects that land cover or land cover change has on climate. Additionally, there is a lack of research that analyzes what impact land cover has on climate on a regional scale. This study addresses both of these issues and further establishes the magnitude of land cover's impact on climate through a real-world, meso-scale study in the Southeast.

The **goal of this thesis** is to determine the impact of forest cover on the climate of the southeastern United States. To meet this goal, the climatological record of contiguous groups of counties in the piedmont area of the Southeast that have experienced varying levels of land cover change will be compared. Variability

between county groups and within county groups will then be analyzed and interpreted to determine meaningful differences. Specifically there are five objectives in this research:

Objective 1: To develop a method to determine spatially and temporally contiguous county groups of forest cover from US Department of Agriculture (USDA) forest surveys.

Objective 2: To determine the impact of forest cover on air mass character and frequency.

Objective 3: To determine how forest cover alters the precipitation regime of these county groups.

Objective 4: To determine how forest cover influences air temperature.

Objective 5: To determine how forest cover alters the moisture regime during times of vegetation stress.

Chapter 2

BACKGROUND

The scholarly literature on reforestation's impact on climate has historically been rather sparse. The complex nature of land surface interactions with the atmosphere along with the relatively slow rate of land surface change on a scale large enough to impact climate have made direct observations of the land surface's impact on climate difficult. This chapter gives a detailed review of past research pertaining to land cover change and in particular the effects of forest cover change on climate.

2.1 Land Cover Effects on Climate

2.1.1 Precipitation

Early studies investigating the land surface's impact on climate focused on finding observational evidence to suggest that changing the land surface resulted in different meteorological conditions compared to the natural environment. Often the motivation for these studies was a desire to determine the feasibility of altering landscapes in order to increase precipitation over an area.

Black and Tarmy (1963) and Malkus (1963) first investigated the effects of land surface modification on the enhancement of convective precipitation. Black and Tarmy explored the theory behind and practicality of increasing precipitation by covering large areas with asphalt. Their analysis showed that large asphalt areas produced 'thermal mountains' of air warmer than the surrounding air. These thermal mountains had as great of an effect on precipitation enhancement as topographical mountains. The authors concluded that the best location for asphalt coatings would be near coastal areas or on tropical islands and that each acre of asphalt would result in three acres of new arable land.

Malkus (1963) studied the effects of cumulus cloud development resulting from island heating in an arid portion of the Atlantic Ocean. The study focused on the island of Anegada in the West Indies. Malkus found that the island did indeed act as a thermal mountain and caused some convective precipitation to fall downwind from the island over the ocean. From these results, Malkus concluded that asphalt coatings over large areas, given the right location and meteorological conditions, would produce rainfall.

Anthes (1984) examined the theoretical basis for enhancing precipitation based on land cover. He hypothesized that convective rainfall could be enhanced in semi-arid areas by generating mesoscale circulations through reforestation, a more environmentally appealing proposition than hundreds of acres of asphalt. Anthes proposed planting vegetation in uniform bands that are roughly 20 km wide by 100 km long. The vegetation would increase surface roughness, deepen the planetary boundary layer (PBL) and increase evapotranspiration. Theoretically, these changes would lead to increased precipitation.

2.1.2 Soil Moisture/Boundary Layer

Pinty et al. (1989), investigated meso-scale fluxes at the border of a forest and field using modeled and observed latent and sensible fluxes and evapotranspiration data as part of the HAPEX-MOBILHY experiment. Three sites were examined in southern France: maize growing over moist soil, mature oats over dry soil, and a conifer forest over moist soil. The study focused on the latent and sensible heat fluxes, and PBL height over the neighboring land surface types and the resulting changes in wind speed, vertical velocity, turbulent kinetic energy, shear production, potential temperature, and water vapor. The authors found a forest-breeze occurred at horizontal scales of 100-200 kilometers as a result of the lower Bowen ratio over the forested area. The authors also found that soil moisture played a significant role in creating or inhibiting the meso-scale fluxes experienced at these sites.

Blyth et al. (1994) used similar data to investigate the impact of increased evaporation and soil moisture in a forest canopy on precipitation. They found a stable boundary over the forested area that resulted in a negative sensible heat flux which helped to sustain evapotranspiration. This, combined with a large wind shear that developed over the forest provided the necessary energy to increase rainfall from a frontal intrusion by 30%.

2.1.3 Temperature

Reforestation changes two competing processes that impact air temperature – evapotranspiration and albedo. Greater evapotranspiration leads to lower temperatures in forests (although in some cases evapotranspiration will be higher over croplands), while lower albedo in forests leads to higher temperatures

(Gibbard et al. 2005). Numerous climate models have confirmed the impact of these effects at global (Myhre 2003), continental (Bonan 1997), and regional scales (Pitman et al. 2003). Studies based on the observational record are less common and have addressed how these boundary-layer processes affect temperature.

Rubin et al. (1990) examined the effect of land surface characteristics in Oklahoma on summer temperature and cloud formation. Using satellite measurements of vegetation strength (as calculated by the Normalized Vegetation Index (NDVI)) and a simple algorithm to estimate sensible and latent heat flux, the authors found greater cumulus cloud formation over of harvested wheat fields compared to highly-vegetated forested surfaces. In addition, higher temperatures were found over the harvested areas because of higher sensible heat flux and lower evapotranspiration. The results suggest that the effect of higher albedo in non-forested areas was not large enough to offset the lower evapotranspiration rates and led to higher temperatures. The dry and warm atmosphere then led to cloud formation as air parcels rose to the lifting condensation level.

Bonan (2001) used historical land cover and station data to determine the impact of land cover change on temperature. Bonan focused on the Northeast and the Midwest in the U.S. for the study because agriculture expanded in the Midwest and contracted in the Northeast during the last century. The results showed higher than expected diurnal temperature ranges (DTR) in the Northeast and lower than expected DTR in the Midwest. He attributed at least part of these differences to divergent land cover characteristics in these two areas (i.e. high amounts of forest cover in the Northeast) that resulted in lower albedo and warmer temperatures in the Northeast.

Englehart and Douglas (2005) found the opposite effect of land cover change in Mexico. Large-scale deforestation and agricultural intensification are occurring in Mexico, which also causes an increase in surface albedo as reasoned by Bonan (2001). However, no corresponding cooling effect in Mexico was found. The results in fact showed an increase in DTR of roughly 0.3 ^{o}C/decade over the past 30 years. The authors believe that contrary to the temperate US, the land cover changes in Mexico result in less evaporative cooling at the surface which masks and dwarfs any cooling effect due to albedo changes (similar to results found by Bounoua et al. 2002 when modeling Amazonian deforestation).

2. 2 Modeling Land Cover Impacts on Climate

There are two major advantages to using a model to study the effects of land cover changes (LCC) on climate versus examining the actual climate record. First, models give the researcher the ability to control both the spatial and the temporal scale of the study. If the model is powerful enough, and the researchers have the time and the necessary initial dataset, they can begin a model at any time in the past or run a model for any time period into the future. Computing power has advanced to the point where grid resolution is high enough that accurate models of the climate system are available at global, meso, and micro scales. The second advantage is their ability to easily execute control versus perturbed simulations of the climate system. That is, models take the 'normal' initial conditions and perform a model run to establish a baseline climate record. The perturbed run is then executed by changing some parameter or parameters in the model and running the model with the new initial conditions.

It is impossible to use the actual observed climate record for this type of experiment since the climate system is in essence one long experiment running continuously. Proxies must be found to make comparisons (either spatial or temporal proxies) that create uncertainties in the results that have to be accounted for in any study. Models do not require proxies for comparisons since the same experiment can be run over and over again with an infinite number of different model scenarios.

The first major study using computer models focusing on LCC effects on climate was by Charney (1975). Using a Global Climate Model (GCM) with a resolution of 4^{o} X 5^{o}, he simply raised the albedo of the Sahara in the model from 14 percent (control) to 35 percent (perturbed) over a 7-week period in the summer and compared the precipitation in the control model run to the perturbed run. The model results showed a significant decrease in precipitation, cumulus cloud cover, and temperature in the high albedo Sahara. The authors concluded that over-grazing the Sahel could cause an increase in albedo similar to what was used in the model resulting in decreases in Sahara and Sahel precipitation.

Many modeling studies in the 1980s and 1990s focused on the effects of tropical deforestation on climate, particularly deforestation in the Amazon Basin. Shukla et al. (1990) employed a General Circulation Model (GCM) to remove most of the Amazon rainforest and replace it with pastureland in a hypothetical total deforestation of the Amazon basin. Key findings were an increase in air and soil temperatures (0.5^{o} – 3.5^{o}/year) and a decrease in precipitation (200-800 mm/year) and evaporation (200-400 mm/year). In addition, the total length of the dry season was lengthened as a result of the deforestation.

Shukla et al. (1990) assumed total deforestation in the model parameter rather than the more realistic process of deforestation in the form of forest fragmentation. Giambelluca et al. (2003) studied the microclimate of a forest patch in the Amazon in part to address this issue. Their results indicated that the edge effects of the clearing caused greater evapotranspiration to occur indicating that regional evapotranspiration could also increase. This situation is similar to what is experienced in many places in the Piedmont where forest patches are surrounded by deforested areas. These areas have the potential to experience greater evapotranspiration, convection, and possibly precipitation.

Pielke et al. (1999) modeled the impact of anthropogenic changes on Florida's climate over the past century. Using the regional atmospheric modeling system (RAMS) developed at Colorado State University, the authors focused on three summers (1900, 1973, and 1993) in Florida using three different land covers. The model found a 9 percent decrease in precipitation in the 1973 landscape and an 11 percent decrease in precipitation in the 1993 landscape over the state. Most of the land cover changes were from forest to urban areas or forest to agricultural areas. The few observational records available were consistent with the precipitation findings in the study, giving credence to the model results. However, the model showed increases in temperature over time which were not consistently found in the observational record.

Wang et al. (2003) investigated the impact of land cover change on the June meteorology of China using the meso-scale model MM5 (Grell et al. 1995), a regional climate model (RCM). The majority of the land cover change that occurred involved changing forest cover to short-grass or cropland. The authors used two

major land-cover modifications in the model grid based on historical land use: forest to short-grass or crops and short-grass to crops. The MM5 indicated that areas changed to crops or short-grass have reduced leaf area indices (LAI), higher albedo values, significantly lower roughness lengths, reduced root zone depth, and a higher fraction of roots concentrated in the top 0.1 m of the soil. The model was run for one month (June) for every 50th year between 1700 and 1990. Averaged results showed increases in both air and ground temperatures, the sensible heat flux, and decreases in the latent heat flux and the root zone soil moisture. The effect of the increase in temperature and the smaller latent heat flux was also experienced in the atmosphere where the 'drying out' of the air due to the land cover changes continued. The authors concluded that land cover changes do indeed have the potential to impact China's climate and more studies are needed to verify and quantify the relative impact compared to other climate forcings, particularly greenhouse gasses.

While increased computing capabilities led to an increase in the use of models to determine the effects of LCC on climate, they also led to studies dealing with direct observations of meteorological and climatological changes caused by LCCs. In particular, the growing reliability and dissemination of satellite data helped researchers make better comparisons of LCC effects on climate over large areas and over longer time periods.

2.3 Satellite Observations

Early satellite studies focused on the theory as to why land cover change would affect climate, and the studies that were conducted in the field were limited as to how much of an area showed observable changes, and the time period length over which changes were seen (i.e. Malkus 1963). With access to satellite data that

monitor land cover changes (e.g. NDVI data), researchers had the ability to study large geographic areas and make valid comparisons about the meteorological differences arising from land cover heterogeneities.

Carleton et al. (1994) used satellite observations to document the role of land-surface conditions on cloud convection during the 1988 summer drought over the Midwest. A 1^{o} X 1^{o} grid was created over the Midwest to analyze satellite data depicting the behavior of clouds as they formed over different land-cover types. The summer of 1988 (drought) was compared to the summer of 1987 (no drought) in order to better place the 1988 results in context. The results showed that NDVI pixel values over the study area were effective in determining land cover types. This was borne out by comparisons with United States Geological Survey (USGS) land use and land cover maps. Statistically significant differences in NDVI pixel values were found irrespective of surface and soil-moisture conditions. At the same time, there was an absence of significant differences in the NDVI pixel values for vegetation of the same class.

Carleton's study (Ibid) showed that once the NDVI values for different land surface types were known, statistical relationships could be established between different climatological variables. A negative correlation was found between NDVI values and surface temperature. In addition, a statistically significant one-month time-lag correlation between surface NDVI and convective cloud frequency was found for both 1987 and 1988, suggesting, according to the authors, that convective activity over the Midwest in summer may respond to the condition of the land surface established in late spring or early in the summer. The two broad groups of land surface types present were areas with low NDVI values, high surface temperature, greater moisture stress,

and low convective cloud frequency associated with cropped surfaces and surfaces with high NDVI values, low surface temperature, less moisture stress, and higher convective cloud frequency associated with forested areas. These differences were amplified during the 1988 summer drought as compared to the summer of 1987 where the differences in NDVI values between land surface types were not statistically significant.

O'Neil (1996) expanded on Carleton et al.'s study and used GOES satellite imagery on a 1^{o} X 1^{o} grid to investigate relationships between land cover type and convective cloud formation during summers of 1985 and 1989 in the Midwest. Using non-parametric differences of means tests, O'Neil was able to show that at the climatological scale, mountainous deciduous forests in the Appalachians and flat coniferous forests in Ontario have more cloud cover on weak synoptic flow days than other surface types. In addition, surface moisture and atmospheric moisture did not significantly alter spatial distribution of convective clouds in his small sample.

2.4 Research Deficiencies

While models have advantages over observations for analyzing LCC impact on climate, there are disadvantages as well. Models do not include all aspects of the climate system. Furthermore, the results of the model may not be what actually occurs because of difficulties in estimating natural phenomenon and due to limiting grid resolution, especially with large-scale general circulation models (GCMs). Higher resolution RCMs provide more detail spatially and temporally and have been useful in determining LCC impact on climate, but there are problems with the results that are generated with these models as well. The main problems with RCMs are the difficulties with integrating the climate dynamics obtained in the RCM, with those

outside of the RCM. Errors will result because of the lateral boundary conditions near the models edge, whether those conditions are from climatological observations or from a GCM (Denis et al. 2003). All of these problems with RCMs and GCMs are indicative of the need to maximize computational efficiency because of time and monetary constraints.

Denis et al. (Ibid.), focused on these problems by running experiments with a down-scaled RCM (the Canadian Regional Climate Model) inside a GCM over eastern North America for four Februaries. Their results revealed maximum allowable differences in spatial and temporal resolution between the RCM and the GCM that provided the lateral boundary conditions. The authors noted however, that even though the RCM performed very well with these conditions, it would not perform as well in areas without fixed spatial features that affect the dynamics of the model (e.g. the Great Lakes and the Rocky Mountains), or during different times of the year with weaker synoptic flow (e.g. summer).

2.5 Land Cover Impacts in the Southeast

No studies have dealt with the impact of reforestation on climate in the Piedmont region of the Southeast using the observed climate record. Pielke (1999), studied how LCC reduced precipitation over the last century, but the study was limited to Florida. In addition Bonan's (2001) and Englehart and Douglas's (2005) studies only considered the Northeast/Midwest and Mexico, respectively.

Pielke et al. (1997) is the most closely related study. The authors used USGS land cover data in a RCM to examine the effects of land cover heterogeneities on cloud formation and convective precipitation over the Atlanta, Georgia area. The regional climate model was used in a case study for one day, July 26, 1987, and had a

very fine spatial resolution of 3 km. The authors found that the heterogeneous nature of the landscape (i.e. forest, agriculture, and urban areas all near each other), led to larger amounts of convective precipitation than would have been present under homogeneous land cover conditions such as total forest cover. Thus, the land cover heterogeneities led to the creation of mesoscale circulations during weak synoptic forcing.

Bonan (1997) used the NCAR Community Climate Model (CCM) to study LCC impact on climate for the entire United States since 1700, but the temporal and spatial resolution was too coarse to draw strong conclusions from the results. Gibson and Vander Haar (1990) examined cumulus cloud formation as a result of geographic features in the Southeast. Their study focused on using satellite images from the summer of 1986 to determine the affect of mountains and the Gulf of Mexico on forming clouds during the day. They concluded that small-scale features did not play a significant role in cloud formation, but the focus of their study was not on how the land cover itself affects the meteorology of the region. Moreover, the study was on a short time-scale and did not examine long-term effects of land cover change on climate.

2.6 Conclusion

The review of the literature shows that there are numerous uncertainties as to the magnitude and the direction of change in climate caused by reforestation. The competing processes of albedo change and evapotranspiration that are seen in many areas with large-scale forest cover changes can lead to contradictory findings. These results reinforce the fact that the effect of land cover change on climate will vary across the globe. By analyzing the impact of reforestation on the climate of the

Southeast, this study adds to our understanding of how these processes affect the meso-scale climate in a region that has undergone extensive reforestation over the last century and yet still has large swaths of agricultural land.

Chapter 3

METHODOLOGY

To determine the impact of reforestation on climate in the Piedmont, two types of data are needed: land cover data, and climatic data. Land cover data is used to determine forest cover changes through time and climatic data is used to quantify air mass characteristics and estimate soil moisture. This chapter contains a description of: (1) the study area, (2) the forest cover data and climate data, (3) the clustering procedure to create contiguous groups of similar counties, and finally (4) the methods to determine air mass character and soil moisture over a grid of the study area.

3.1 Geography of the Study Area

The study area, the piedmont and upper coastal plain area of the southeastern United States (hereby referred to as the Piedmont) is shown in Figure 3.1. The Piedmont roughly encompasses the region between the lower coastal plain and the Appalachian Mountains. Several factors combine to make this a particularly suitable area to determine the effects of reforestation on climate. Within the Piedmont there are extensive areas of reforestation, deforestation, agricultural abandonment, and areas that have had little change in land surface cover type over the past six decades.

The period of study for this research is the summer months of June, July, and August from 1948 to 2001. These years are chosen because of the restraints of the

available air mass and climatic data. However this time period does include a fairly large portion of the forest cover change experienced in the region over the last century. Only summer months will be analyzed because of the absence of synoptic activity in this area during this time of year. This is advantageous because increases in precipitation due to reforestation would most likely come from the creation of mesoscale fluxes. This would lead to more convective precipitation (the dominant precipitation mechanism in the summer) as opposed to frontal precipitation (the dominant precipitation mechanism in other seasons).

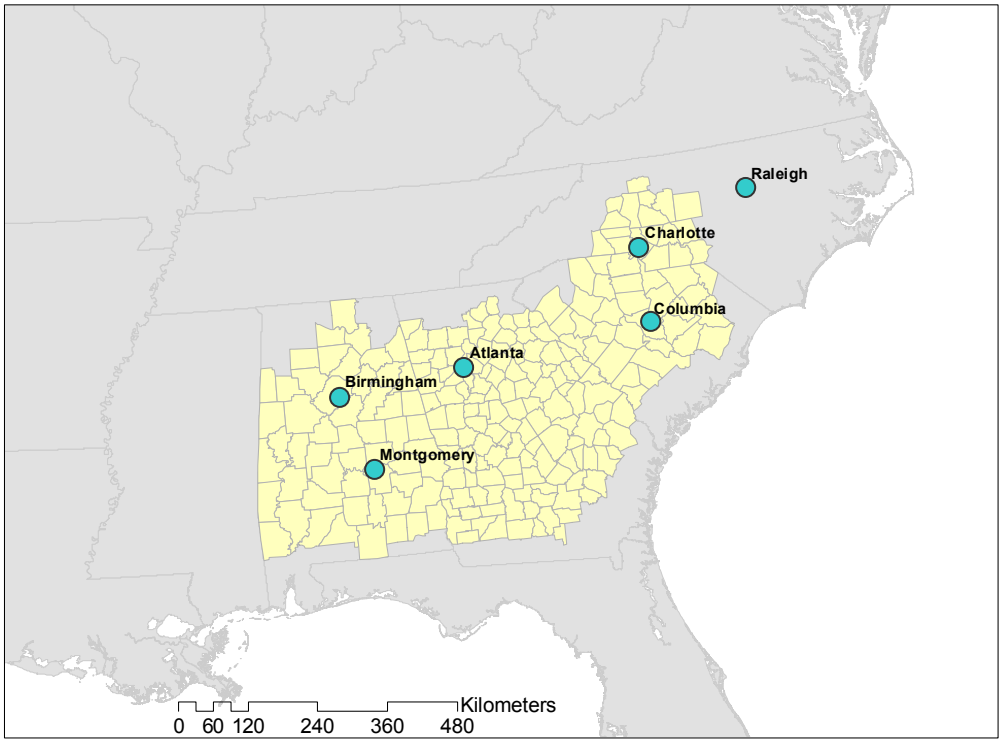

Figure 3.1. Study region for this thesis.

Furthermore, a smaller number of air masses dominate in the summer months compared to other seasons. This results in a larger sample of days for statistical analysis for the air masses that do occur. Finally, examining only summer months as opposed to all seasons eliminates the need to filter out the seasonal cycle when determining the effects of reforestation on air mass character.

Figure 3.2 shows the mean summer temperature in the Piedmont and indicates that the range of mean temperatures over the vast majority of the study area is only one or two degrees. The selection of the Piedmont for the study area and the absence of the Appalachian Mountains greatly reduces the range of temperatures that are experienced in the study area. This homogeneity of the temperature regime helps to facilitate comparisons between different areas of the study area.

Similar homogeneities exist in the spatial distribution of summer precipitation (Figure 3.3). Large portions of the Piedmont experience precipitation amounts between 300 and 350 mm during the summer. The regional maxima in the Appalachians and along the coast are outside of the study area. There is a steady increase in precipitation of between 50 and 100 mm in the study area as the distance to the coast decreases. This increase will be accounted for by limiting precipitation comparisons to areas that experience similar rainfall amounts in the summer.

In addition to being climatologically homogeneous, the study area is also topographically homogeneous. Figure 3.4 represents elevation values from a Digital Elevation Model (DEM) of the southeastern U.S. (USGS 2000). The Piedmont study area is generally 100 to 500 meters above sea level and lacks sharp contrasts in elevation found in the Appalachian Mountains. Avoiding the Appalachians is important because of the localized climatic conditions that occur due to the mountains

and valleys. The study area also minimizes the strongest effects of the Atlantic Ocean since it is located far enough inland that for the most part, sea breezes are not a major determinant of air mass character and climate.

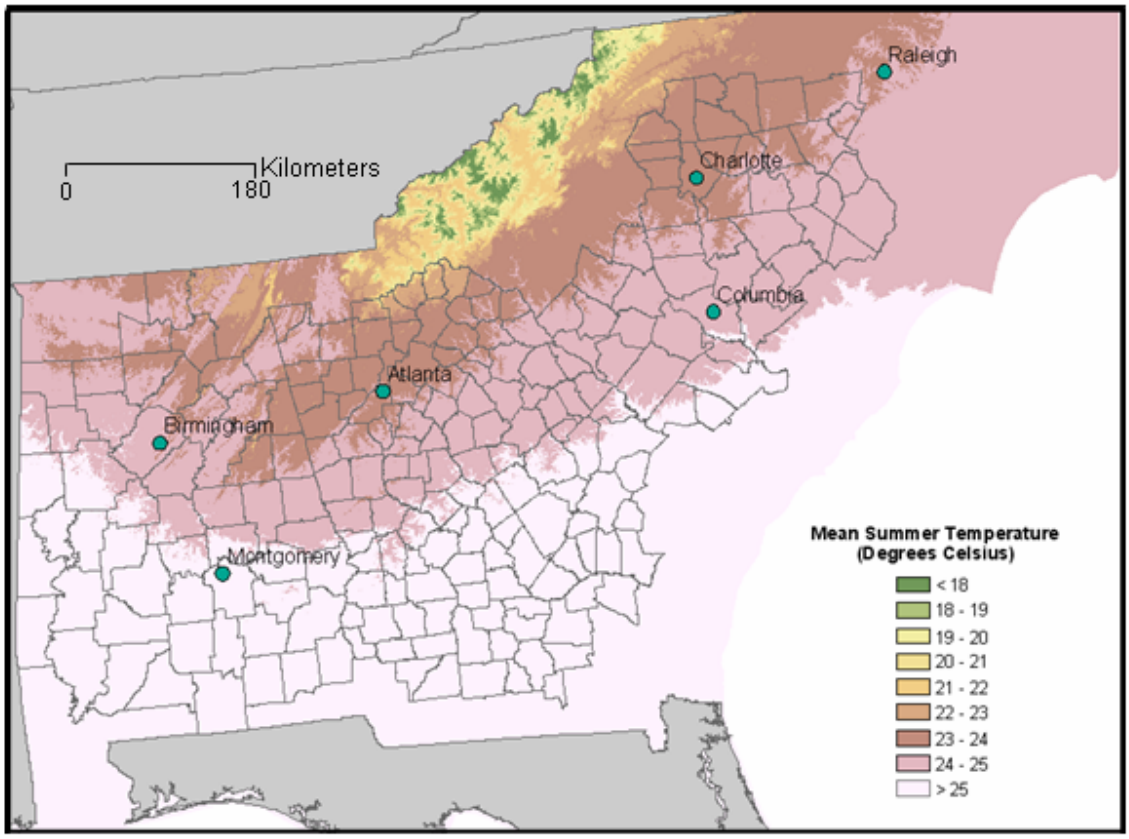

Figure 3.2. Mean summer temperature (1960-1990) for the southeastern U.S.

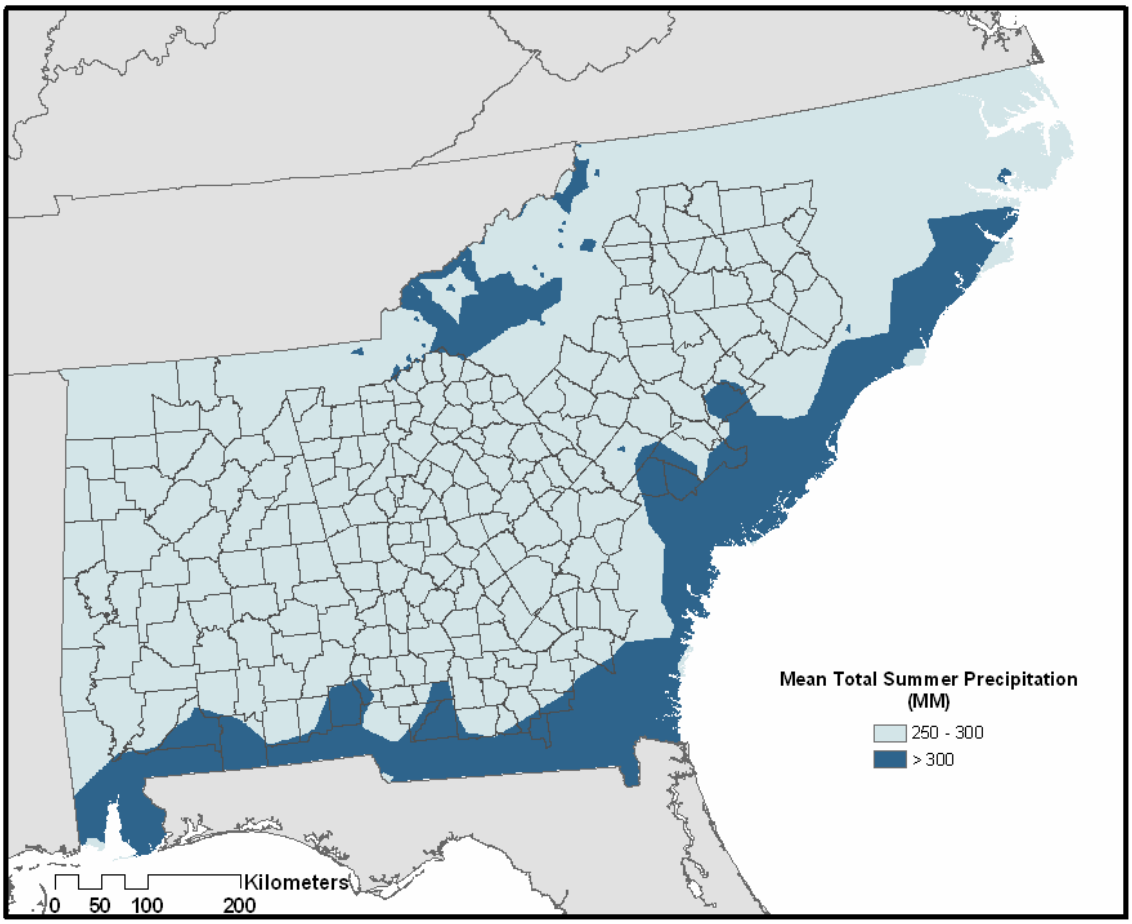

Figure 3.3. Mean total summer precipitation (1960-1990) for the study area.

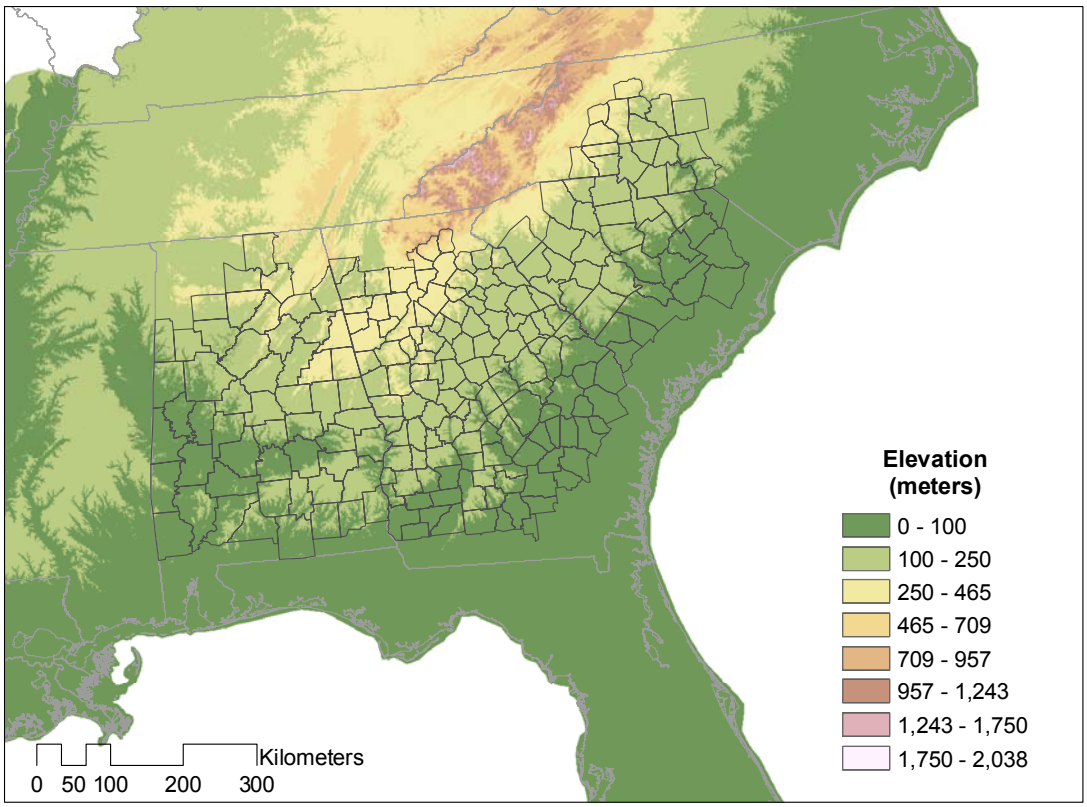

Figure 3.4. Topographic homogeneity in the Piedmont study region.

Metropolitan counties in the Piedmont were excluded from this study for two reasons. First, the analysis is made simpler because the absence of these counties eliminates effects of the urban heat island. Second, in future research, differences in air mass character in urban areas caused by reforestation should be studied, but those differences should be examined on a higher temporal and spatial resolution than what is available for this study.

3.2 Historical Land Cover in the Piedmont

Except for small areas of aboriginal agriculture, the original pre-settlement land cover of the Piedmont was almost entirely forest (Nelson 1957, Cowell 1995). Rapid clearing of land began when Europeans settled the Piedmont in the 18th century and continued until the early 20th century. However by 1920, the arrival of the boll weevil in cotton fields, soil exhaustion, and depressed economic conditions caused widespread abandonment of agricultural areas (Haney et al. 1996). These abandoned areas reverted back to forest containing early successional stands of pine followed by fire-intolerant species of trees (i.e. hickory and white oak) (Cowell 1998).

The Southern Forest Resource Assessment (Wear and Gries 2002) detailed how the southeastern forests first encountered by Europeans in the 17th and 18th centuries were not 'climax' forests of natural vegetation. Native Americans had modified their surroundings to suit their needs as all humans have done. With a significant decline in the Native American population after 1500 forest expansion and canopy closure occurred throughout the Southeast. Once Europeans began in earnest to settle the interior of the country, forest cover declined precipitously as land was cleared for agriculture, construction, and pine resin production.

Forest cover continued to decline throughout the 18th, 19th, and early 20th centuries reaching its lowest level around 1920 (Pinder et al. 1999). It was at this time that the disadvantages of clear-cut logging practices without reforestation became apparent as forest resources were exhausted. Modern forestry practices were ultimately implemented. Thus, the abandonment of both farms and destructive forestry practices in the Southeast triggered a rapid process of reforestation. The process accelerated during the Great Depression in the 1930s. Migration out of rural areas rose, but the federal government also contributed to the reforestation of the Southeast by both purchasing land for national forests and funding extensive reforestation programs.

By the 1940s logging had begun again, but the new forestry management practices resulted in increases in large-scale reforestation projects and heavy fire-suppression. As a result, forest acreage continued to increase and eventually peaked in the late 1960s and early 1970s and then began to decline or stabilize in many areas (Figure 3.5). Stability in forested acres resulted from increasing urbanization in the Southeast as well as maturation of pine stands that were ready for harvest after roughly 40 years. Further increases are also evident over the last decade as forests regenerate and agriculture continues to decline in importance. Currently approximately two-thirds of the land surface in the Piedmont is forested.

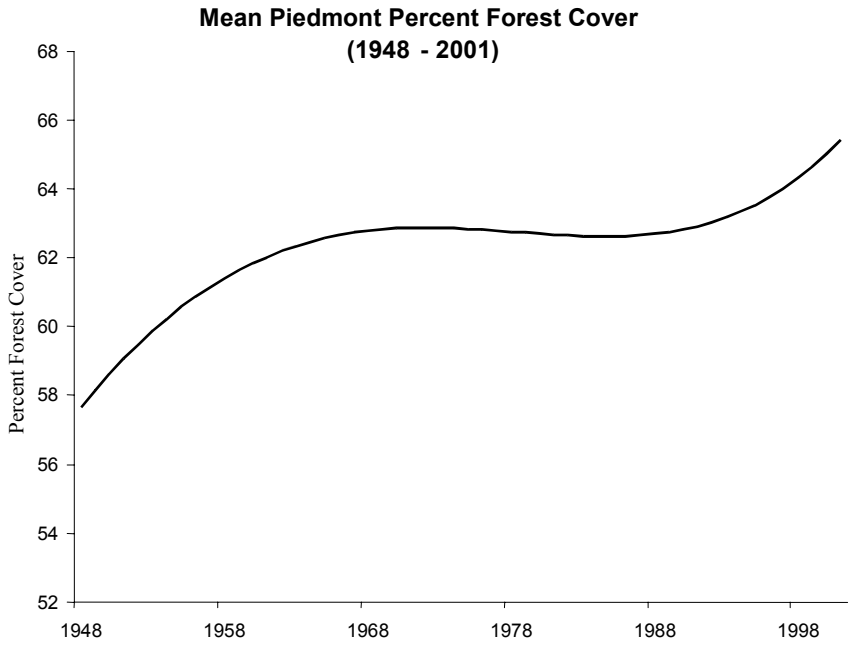

Figure 3.5. Mean Piedmont forest cover 1948 - 2001 as a percent of total area.

Reliable estimates of forest cover based on statistical sampling in the Piedmont began in 1938. Since that year, the United States Forest Service (USFS) has performed decadal surveys of forest cover on the county level based on both aerial photographs and ground surveys. Satellite data are ideal because of the high spatial resolution but the period of record only extends back to the early 1970s when reforestation had already peaked in many areas of the Piedmont. These surveys provide the long-term forest cover data needed for this study.

3.3 Forest Cover Data

Forest cover data were obtained from the USFS forest survey statistics. These surveys are conducted every eight to ten years for each county in the sub-region and provide data on forest cover at the county level. Each state is divided into three to five sub-regions and surveyed (Figure 3.6). Alabama, for example, has six sub-regions with forest surveys conducted in 1936, 1953, 1963, 1972, 1982, 1990, and 2000. The dates of the surveys vary from one sub-region to another, but usually all the sub-regions in a state are surveyed at about the same time and all of the states are surveyed at least once a decade. It is important to note that some survey years are not available for certain sub-regions. For example, the most current survey of the North Carolina Piedmont region has not been released yet, and the 1964 survey data for North Carolina are no longer available.

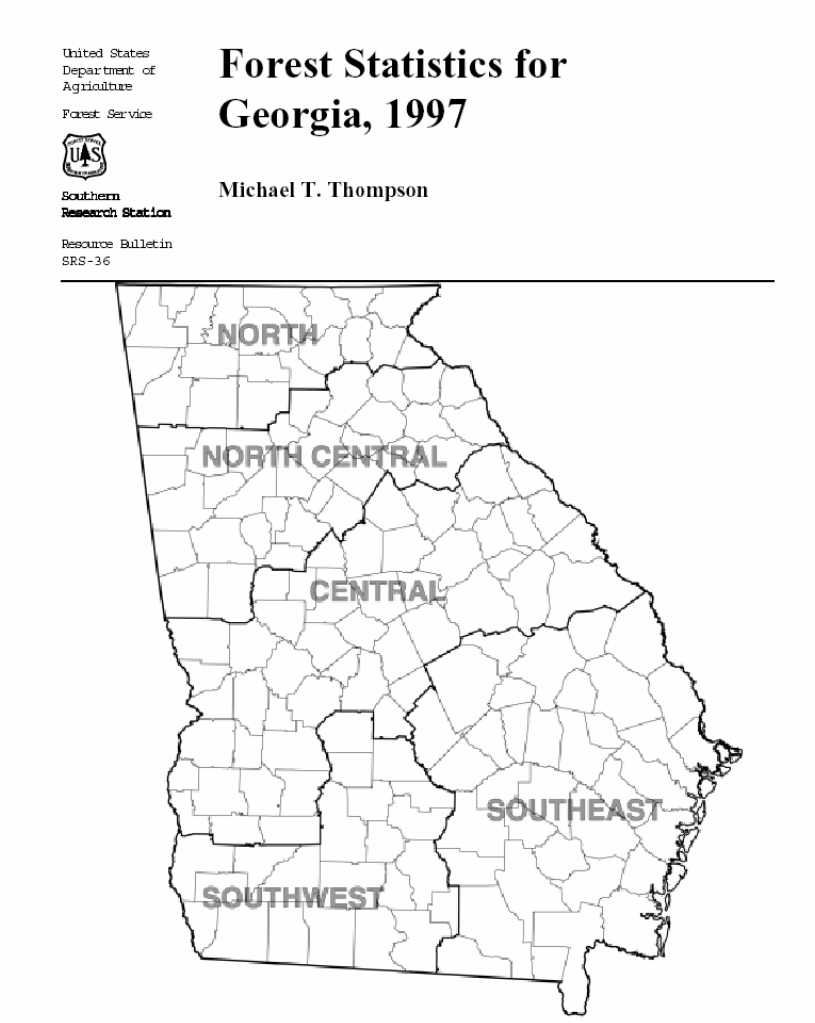

Figure 3.6. U.S. Forest Service forest survey sub-regions for Georgia.

The sampling procedure the Forest Service uses to determine forest cover is a three-step process. Land cover is classified based on thousands of 16-point

sample clusters[1] that are systematically spaced on aerial photographs. A sub-sample of these clusters (5-10% of all the clusters) is ground-checked, and finally, an error matrix is created between the initial estimate and the reclassification to uncover changes in land cover since the aerial photos were taken and to correct for errors in the first classification (Thompson and Sheffield 1997).

While the USFS recommends using these statistics on a state or survey unit level (Ibid.), the sampling error for each county range from one to ten percent which is considered very good for remotely sensed data (Campbell 1996). Therefore, the accuracy of these data was deemed sufficient for this study. Table 3.1 shows an example of a forest sample survey from the southeast region of Georgia in 1971. Table 3.2 shows the sampling error for the same region.

[1] The number of sample clusters depends on the size of the forest survey unit. Usually, each state is divided into survey units of roughly 20,000 km^2. Survey units of this size normally have at least 30,000 sample clusters.

Table 3.1. Example of forest survey statistics. This table is for counties in southeastern Georgia as determined from a 1971 USFS forest survey.

County	All Land	Forest Land				Nonforest Land
		Total	Commercial Forest	Unproductive Forest	Productive Reserved	
	thousand acres					
Appling	328.2	233.8	233.8			94.4
Atkinson	202.9	161.9	161.9			41.0
Bacon	187.5	117.3	117.3			70.2
Brantley	296.1	254.3	254.3			31.8
Bryan	282.8	227.8	227.7	0.1		55.0
Bulloch	438.4	242.3	242.3			196.1
Camden	420.2	323.4	320.6	2.3	0.5	96.8
Candler	164.7	88.9	88.9			71.8
Charlton	511.4	492.3	332.2		160.1	19.1
Chatham	289.4	126.5	123.3	0.3	2.9	162.9
Clinch	509.2	489.4	473.4	1.2	14.8	19.8
Coffee	392.0	245.9	244.4		1.5	146.1
Dodge	320.0	201.0	201.0			119.0
Echols	272.0	252.5	251.5	1.0		19.5
Effingham	307.2	247.8	247.8			59.4
Emmanuel	439.0	311.9	311.9			127.1
Evans	119.1	75.7	75.7			43.4
Glynn	282.6	178.9	175.5	0.2	3.2	103.7
Jeff Davis	211.8	155.1	155.1			56.7
Jenkins	224.6	138.0	137.1		0.9	86.6
Johnson	200.3	112.7	112.7			87.6
Laurens	519.0	304.4	304.4			214.6
Liberty	327.4	252.8	252.6	0.2		74.6
Long	257.9	243.0	243.0			14.9
McIntosh	287.8	203.7	200.9	2.8		84.1
Montgomer	151.7	106.2	106.1			45.6
Pierce	218.9	139.2	139.2			79.7
Screven	416.3	244.7	244.7			171.6
Tattnall	315.5	200.2	200.0		0.2	115.3
Telfair	281.4	211.0	210.9		0.1	70.4
Toombs	236.2	137.7	137.7			98.5
Treutlan	123.9	88.5	88.5			35.4
Ware	583.6	510.4	344.9	14.8	150.7	73.2
Wayne	413.4	336.4	336.4			77.0
Wheeler	195.5	143.8	142.9		1.0	51.6
Total	10713.9	7799.4	7440.6	22.9	335.9	2914.5

Table 3.2. Same as Table 3.1, except table shows sampling errors for forest survey statistics for southeastern Georgia in 1971.

County	Commercial Forest area	Cubic-Foot Volume of growing stock		
		Inventory	Growth	Removals
Appling	2.00	12.61	12.68	19.11
Atkinson	1.96	13.99	15.74	21.01
Bacon	3.68	17.61	22.03	28.69
Brantley	0.96	11.96	10.54	24.73
Bryan	1.93	10.80	11.42	21.96
Bulloch	2.08	9.40	10.53	22.16
Camden	1.78	11.73	11.45	24.51
Candler	2.66	23.38	21.05	44.82
Charlton	0.55	12.30	11.75	23.50
Chatham	3.82	15.87	20.17	40.00
Clinch	0.45	9.07	9.54	22.76
Coffee	2.15	11.07	10.20	21.15
Dodge	1.91	10.53	10.95	21.44
Echols	0.93	12.46	11.80	15.98
Effingham	1.69	9.55	8.03	20.54
Emmanuel	1.74	9.63	9.82	21.63
Evans	2.98	23.62	17.29	45.98
Glynn	2.93	17.76	18.23	27.30
Jeff Davis	2.00	13.35	16.34	25.41
Jenkins	2.32	16.82	12.04	30.36
Johnson	2.81	15.13	12.34	31.24
Laurens	1.66	7.03	7.14	19.26
Liberty	2.64	11.04	10.93	17.20
Long	1.13	12.46	13.59	30.58
McIntosh	2.24	11.75	14.90	32.75
Montgomer	2.31	15.38	13.44	36.20
Pierce	2.13	11.47	11.71	29.27
Screven	1.70	10.79	9.87	29.60
Tattnall	1.80	12.84	11.92	27.91
Telfair	1.57	11.96	13.47	22.48
Toombs	4.28	14.62	13.77	28.90
Treutlan	2.29	13.56	11.19	35.75
Ware	1.08	9.85	9.78	21.34
Wayne	1.16	12.04	12.00	18.32
Wheeler	1.83	11.85	12.75	34.04
Total	0.33	2.11	2.10	4.32

the period between survey years. A best-fit polynomial (2nd order or higher) was used to

interpolate missing forest cover data. This algorithm was chosen after examining several different orders of polynomial fits. Lower order polynomials (especially linear trends) were too general and higher order polynomials began to create trends in the data that don't duplicate reality for such a gradually changing variable as forest cover. In particular, a simple linear trend was not appropriate because the data are on the county level, and as such there will be forested areas within the county that are being cut or not cut at any given time. In addition, extenuating factors such as development pressures, agricultural prices, and random natural events (e.g. disease or insect infestation) can all differentially impact the forest cover within a county. Once the best polynomial was fit to the data, each missing year's forest cover was extrapolated from the curve.

Once yearly forest cover values for each county were known, counties were clustered into similar groups based on their forest cover and proximity to each other. Several traditional clustering algorithms such as Ward's method (Ward 1963) and the average-linkage method were utilized (SPSS Inc., Chicago, IL). They all performed reasonably well when clustering the counties into similar groups based on the overall forest cover. However, none of these clustering procedures adequately clustered the data into groups that had similar changes in forest cover through time. Counties that had increasing forest cover over a given time period were often placed in the same group with counties that had decreasing forest cover over the same time and vice versa because they had similar amounts of forest cover.

To create contiguous groups of counties with similar forest cover through time, a hybrid clustering procedure was developed. All counties were clustered into three broad groups (low, medium, and high forest cover) based on their forest cover in

1948 (the first year of this study). The three groups were classified based on the standard deviation of a mean forest cover of 58% for all Piedmont counties in 1948. Counties that had a 1948 forest cover less than one standard deviation below the mean (less than 48% forest cover) were grouped into the low group. Similarly, those with 1948 forest covers between 48% and 76% were in the medium group (one standard deviation below and above the mean), and those greater than 76% forest cover (greater than one standard deviation above the mean) were placed in the high group.

Once the three broad groupings were created, the counties in each group were clustered into categories based on similar forest cover through time. The standard deviation was calculated for each year in each group (e.g. the standard deviation of all counties in the low group in 1954 was 5.58% and 5.64% for 1955). This was done to ensure similarity in forest cover levels between counties for the benefit of the clustering algorithm. Each county was iteratively compared to every other county in the broad group based on the year's standard deviation and the yearly slope-sign (positive or negative forest cover change from year-to-year) of the county.

The slope-sign is either positive or negative, permitting a determination of whether the two counties followed the same trend in forest cover as in the previous year. For example, if one county had a positive slope-sign in 1965, that indicates an increase in forest cover from the previous year, and if the other county under comparison also had an increase in forest cover from the previous year, that is one common year those two counties share. Those counties that were within one standard deviation of each other and had the same slope-sign for at least 40 out of 54 years were clustered into a group. Retaining counties with similar slopes created groups that had very similar levels of forest cover **and** similar changes in forest cover through

time. Figure 3.7 shows an example of a group of clustered counties centered near Dawson County Georgia after the conclusion of the clustering procedure. Each shade of gray represents the yearly percent forest cover for a particular county as estimated from the forest survey statistics. The mean of the four neighboring counties results in the estimated percent forest cover for the contiguous county group (orange).

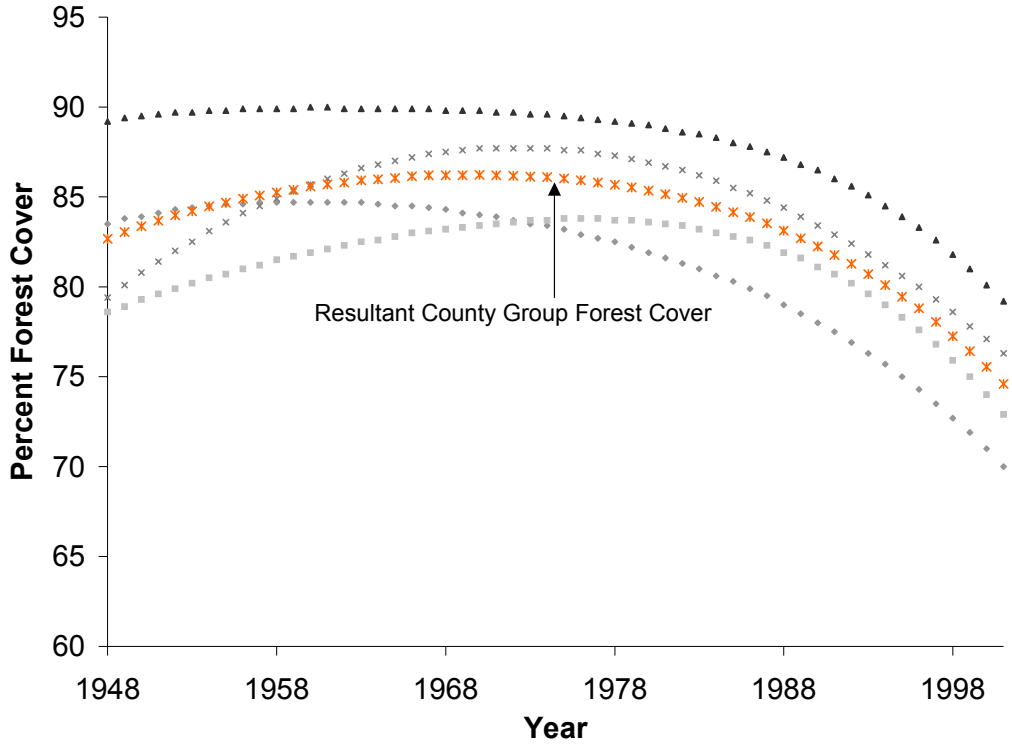

Figure 3.7. Sample result of clustering procedure. Yearly forest cover for four clustered counties (gray shades) and the resulting mean for the contiguous county group (orange).

The result of the clustering was the creation of three categories of forest cover: low, medium, and high forest cover. The county groups that were spatially contiguous to each other were grouped into single contiguous units as shown in Figure

3.8 (this term, along with the term “contiguous group”, will be used to connote a group of counties that are spatially grouped together without any separation). The number of counties in many contiguous groups was reduced due to a lack of long-term climate data in some counties. The procedure for determining which counties were removed from a contiguous group is described in the following section.

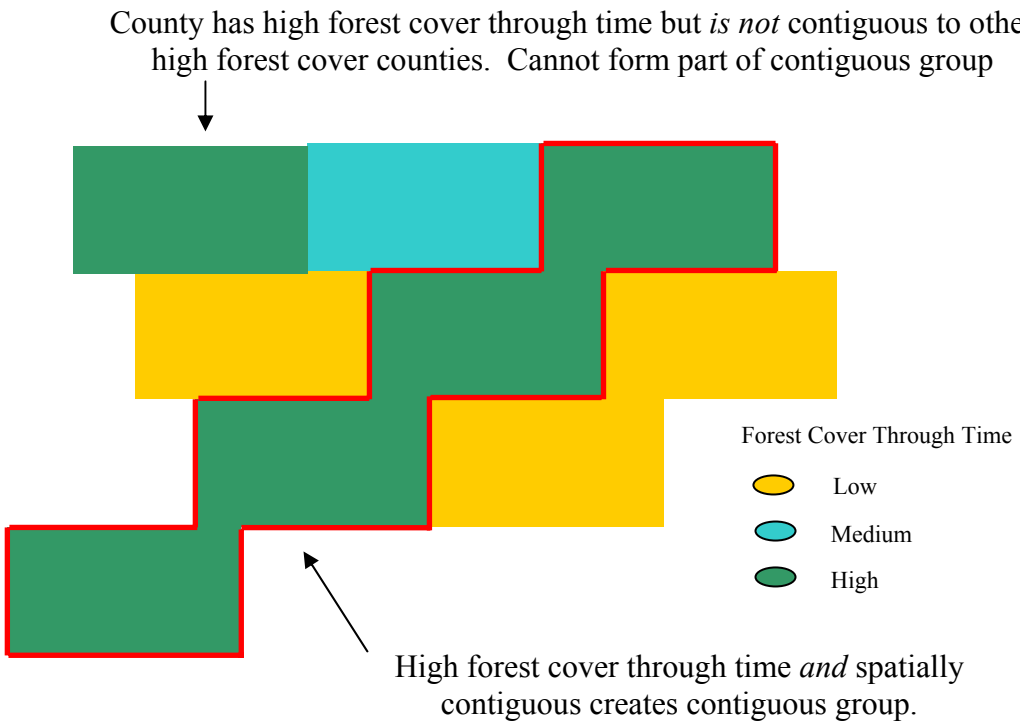

Figure 3.8. Example of a contiguous group or unit of counties.

3.4 Climate Data – Air Mass Analysis

Climate data for June, July, and August are needed to perform both the air mass and soil moisture analyses. For the air mass analysis portion of this study, air mass character was calculated through the use of the Spatial Synoptic Classification (SSC). The SSC is an air mass-based synoptic classification scheme that uses both automatic and manual steps in its identification of air mass types. In the SSC, six basic air mass types are manually identified for North America based on a priori assumptions involving general air mass climatology (Sheridan 2000). The six air mass types identified are:

- **Dry Polar (DP)** – air mass is cold and very dry, similar to cP Bergeron (1930) air mass type.
- **Dry Moderate of Temperate (DM)** – air mass is mild, dry, and often adiabatically warmed and has no definite source region.
- **Dry Tropical (DT)** – air mass is hot and dry and similar to Bergeron's cT designation.
- **Moist Polar (MP)** – air mass is cold and humid and is often accompanied by precipitation (analogous to Bergeron's mP air mass type).
- **Moist Moderate (MM)** – air mass is mildly cool and humid with precipitation.
- **Moist Tropical (MT)** – air mass very warm and humid and is often associated with convective precipitation (similar to Bergeron's mT designation).

The **Transition air mass (TR)** is an air mass type that represents the change from one air mass type to the next.

The basis of the SSC is the selection of 'sliding seed days' that determine the mean character of the air mass at a particular weather station. Thus seed days

allow the SSC to account for differences in season and geography in the determination of the current air mass over a region. For example, a bitterly cold air mass will have a different meaning in Wisconsin than it does in Florida. In general once the air mass reaches Florida it will be modified to such an extent that it will have a completely different set of characteristics that may warrant a change in the air mass assignment. The goal of the SSC is to determine these characteristics in order to assign a meaningful surface air mass type; seed day selection is the mechanism used to execute the SSC (see Sheridan 2002 for further explanation of seed days).

A seed day is an actual day in a station's period of record that contains typical meteorological characteristics of a particular weather type at that location (Ibid.). Sliding seed days are seed days selected in four 2-week 'windows' throughout the year. The four windows shift from station to station to reflect the hottest and coldest periods of the year, and the periods halfway in between. The following meteorological data are required for seed day selection:

- Temperature at 04 h LST
- Temperature at 10 h LST
- Temperature at 16 h LST
- Temperature at 22 h LST
- Dew point depression at 04 h LST
- Dew point depression at 10 h LST
- Dew point depression at 16 h LST
- Dew point depression at 22 h LST
- Mean daily cloud cover

- Mean daily sea level pressure
- Diurnal temperature range
- Diurnal dew point range

Once the sliding seed days are selected, air mass types can be assigned to a station for every day of the year. Assignment is accomplished by comparing the mean station value of each air mass for that particular day to the measured meteorological data for the day. The SSC uses a simple summing of squared *z*-scores to compare mean meteorological values of the air masses to the measured meteorological values for the day:

$$h_k = \sum_{i=1}^{12} \left(\frac{x_i - \mu_{ki}}{\sigma_i} \right)^2, \qquad (3.1)$$

where i is one of the 12 variables listed above for seed day selection (temperature, dew point, barometric pressure, etc.), x_i is the value of i on the particular day being evaluated, μ_{ki} is the derived mean value of i for air mass k from the sliding seed days, and σ_i is the standard deviation of i for air mass k. The resulting h_k score is the amount of difference (the 'error score') between the typical air mass characteristics for that day of the year, and that day's particular meteorological values. The air mass with the lowest h_k score is then assigned as that day's air mass (Ibid.). For more detail on air mass descriptions and the SSC methodology, refer to Sheridan (2002).

The daily air mass calendars produced by the SSC are available for almost every first-order weather station in the United States from 1948 to 2001 and provide

good regional coverage of air mass conditions. Unfortunately, first-order stations are usually in urban areas or near large metropolitan areas. While the network is dense enough to determine which air mass is occurring on a regional basis, the network is too sparse to determine if forest cover change for each contiguous geographic unit is having an impact on air mass character.

No first-order stations are present in any of the contiguous-units that were created from clustered forest data. Therefore, data from National Climatic Data Center (NCDC) cooperative stations (coop stations) in each contiguous unit are needed. Figure 3.9 highlights the disparities in station densities between first-order weather stations and coop stations in the study region.

It should be noted that air masses are mesoscale three-dimensional phenomena, so it is probable that air mass types determined at the first order stations closest to contiguous units are present over the contiguous units themselves.[2] Once air mass types are established on a regional scale, air mass character changes can be determined for each contiguous unit using the coop stations within that unit. It is assumed that these stations will be representative of any air mass character changes due to forest cover *within that contiguous unit*. Conversely, it cannot be assumed that stations *outside* of the contiguous unit will experience changes in air mass character due to forest cover change within the contiguous unit. A hypothetical example is provided in Figure 3.10 where three stations within county group A are used for the interpolation but the first order station outside of this group is not.

[2] This was verified using procedures described later in this report.

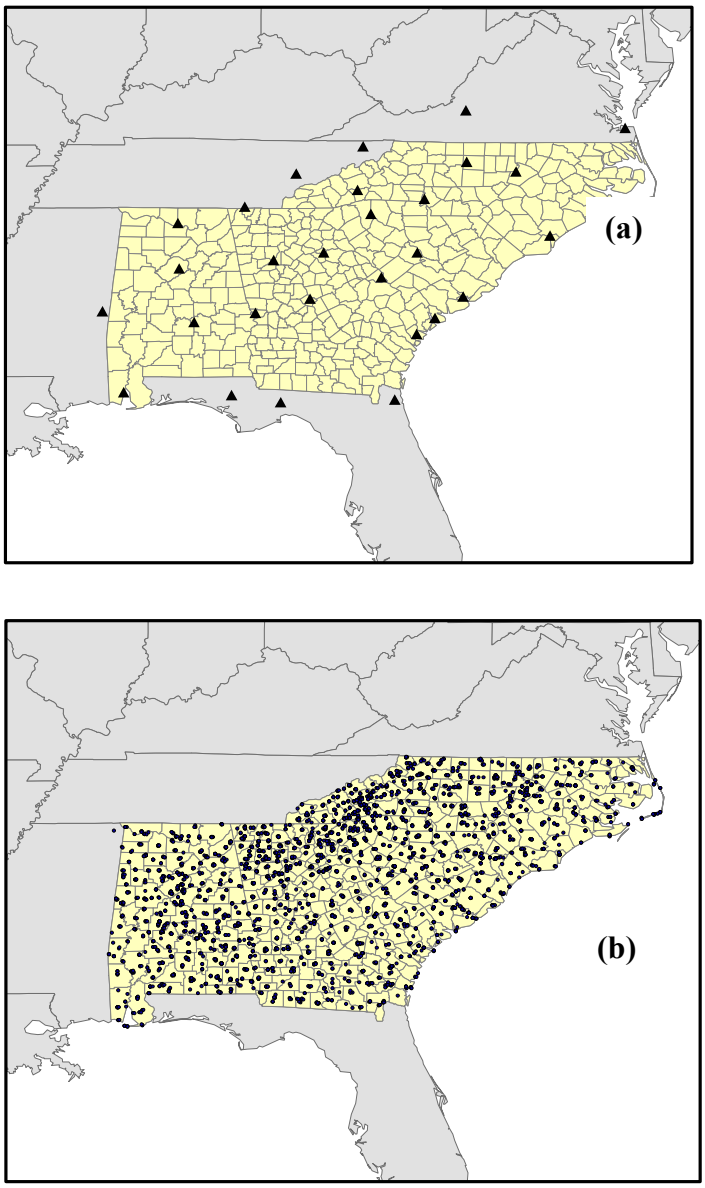

Figure 3.9. NCDC first-order station network (a) and cooperative station network (b) in the Southeast as of 2000.

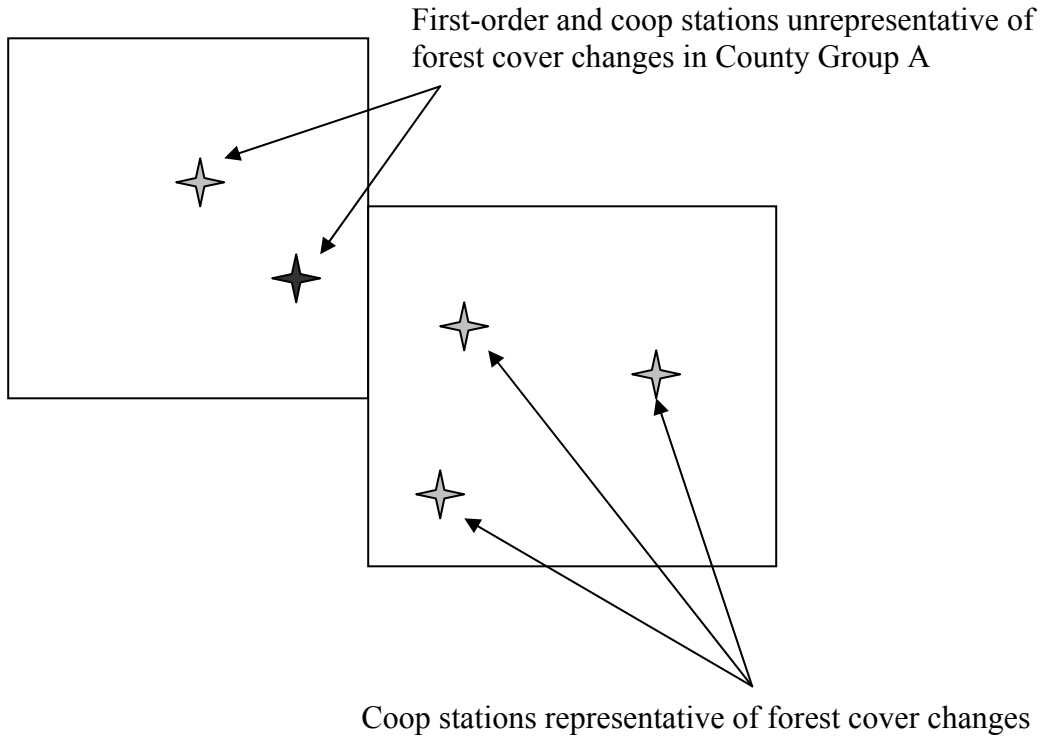

Figure 3.10. Example of use of climate data from coop stations within a county group to capture forest cover changes through time.

There are disadvantages to using coop-stations. For example, these stations only record maximum and minimum daily temperature and daily precipitation. Additionally, the station data are often discontinuous because of bad data or the loss of a station. However, they are the only data available in rural areas over the entire period of record (1948-2001). For a long-term study such as this, they were the only viable data sources, and although they do have disadvantages, the data have gone through quality control measures at NCDC to remove the most egregious problems.

One problem with the coop data not corrected by NCDC is the time of observation. Because the station network relies on volunteers, it is impossible to institute a standard time of day to record the data. Therefore there is large variability between stations and often within a station itself as to when the observations were taken. This creates potential problems for estimating both the temperature and precipitation data. If one station is recording the amount of precipitation that fell for the previous 24 hours at 10 pm and a neighboring station is recording the same variable at 6 am, then the resulting interpolated data will systematically under or overestimate precipitation.

To correct this problem, an algorithm was developed that separated the observation times into two categories. Recorded measurements from observers during the period from 12 pm to 11:59 pm were used as the current day's data. And recorded measurements from observers during the period from 12:01 am to 11:59 am counted towards the previous day's data. In the final dataset there were no instances of observers that took measurements between the hours of 10 am and 2 pm, giving further credence to the corrected data.

After the climatic and synoptic data are acquired, a grid is created over the contiguous-units. This is necessary because the SSC cannot be used with coop stations. It requires four meteorological variables four times daily: temperature, dew point, surface air pressure, and mean cloud cover. Because of this, air mass values must first be determined at surrounding first-order stations, and then interpolated to a grid over the contiguous-units. In effect there are two different interpolation methods used for two different types of data on one single grid; one for air mass data, and one for daily meteorological data.

For the interpolation of the meteorological data, at least three stations are needed for a valid interpolation. If at least three valid stations, or the equivalent of three stations are present (meaning that 90% of summer days from 1948-2001 are covered by three or more stations), then those counties constitute a contiguous-unit that can be utilized for the air mass analysis and the grid interpolation.

This process excluded several contiguous groups created in the forest cover clustering procedure because they did not have a sufficient number of coop stations for interpolation. A hypothetical example of a valid and invalid contiguous group is shown in Figure 3.11. If there were fewer than five contiguous groups in any forest cover grouping (low, medium, and high) after the number of weather stations was accounted for, then the parameters for the forest cover clustering procedure were slightly relaxed until enough contiguous groups were present to make meaningful comparisons. The final parameters for the clustering procedure were the ones described in this chapter.

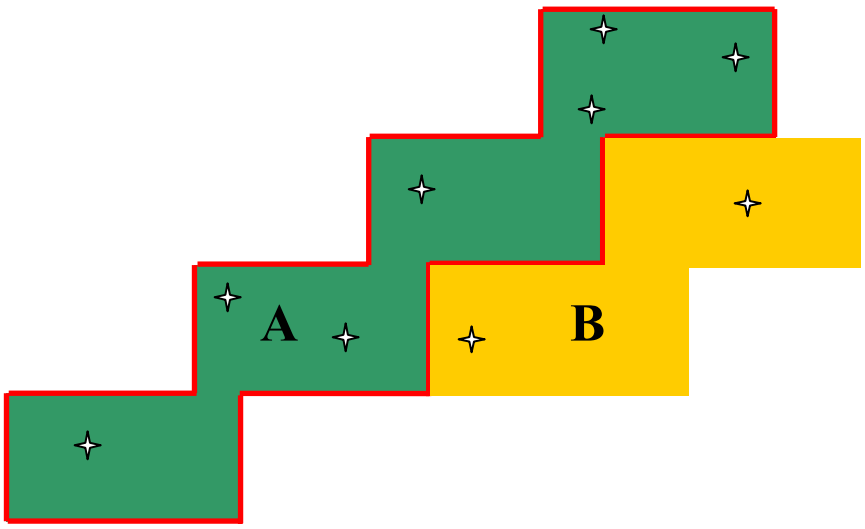

Figure 3.11. Valid (A) and invalid (B) contiguous groups of counties.

Once contiguous groups were finalized, the grid for each group was created. To create this grid, a United States Geological Survey (USGS) Digital Elevation Model (DEM) was used as the baseline for each contiguous-unit. Use of a DEM is advantageous because it is a ready-made high quality grid with elevation data. These data were then used in the interpolation process to correct for temperature changes associated with increases in height. For this study, DEMs with a 1:250,000 scale were used. Each grid cell in the DEM has an elevation in meters that is derived from several topographic map sources, including 7.5-minute and 1-by 2-degree maps, as well as from aerial photographs (USGS 2000).

Unfortunately, the 1:250,000 scale grid is too fine a resolution for the coop station network to resolve. If the grid resolution is too fine, the interpolation procedure can produce interpolated gridded data that do not reflect reality based on the real values from the coop stations. Therefore, a more appropriate resolution was created by re-sampling the grid using ArcGIS™, to a grid cell size of 6-arc seconds (or 1:500,000 scale). A bilinear interpolation method was used to resample the data by calculating a distance- weighted average of the four nearest cells until the specified resolution is reached. Once the final grid was created for each contiguous unit, interpolation of the air mass and climatological data was undertaken.

Normal interpolation methods are not appropriate for air masses because air mass data are nominal data. Instead, a modified neighborhood majority function is used to determine the daily air mass value for each grid cell in the contiguous-unit (Detwiler 1999). This function determines the air mass value for each grid cell based on the most common air mass value within a specified search radius (Figure 3.12).

Using this method, air mass values and boundaries are delineated for every contiguous-unit for every day. The method was slightly modified to discount first-order stations in mountainous areas or near the ocean because of the localized effects these geographic features can have on air mass type and character. In such cases, if the number of available stations in the search radius was less than five, the radius was extended until at least five stations were present. Eventually, all of the contiguous groups had at least six first-order stations that were used to determine daily air mass values.

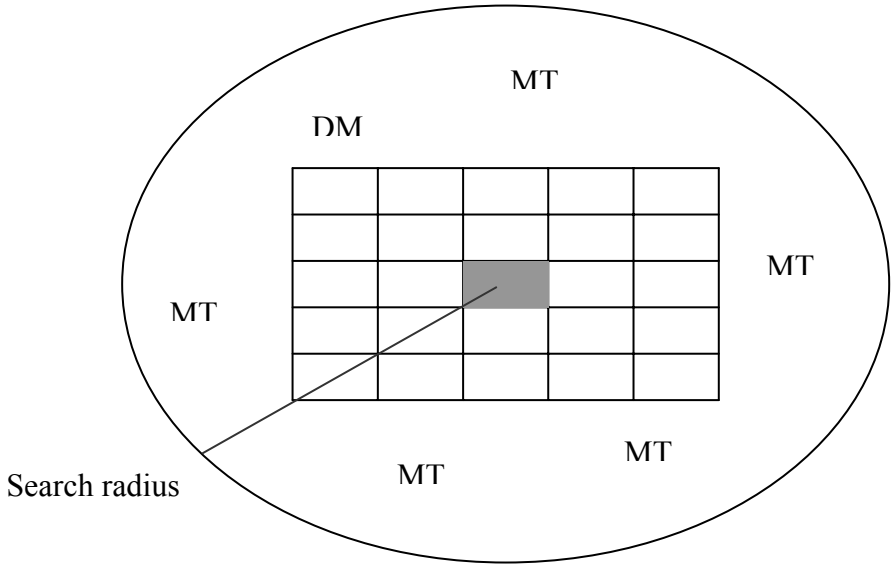

Figure 3.12. Example of neighborhood-majority function for a hypothetical grid cell (from Detwiler 1999).

Verification of the accuracy of the neighborhood majority function was performed through a cross-validation procedure (leave-one-out cross validation). The function uses air mass values from surrounding first-order stations to predict the daily air mass value at a first order station. The predicted value is then compared to the known air mass value at the first-order station to determine how well the model performed. Tables 3.3 through 3.5 show the original yearly air mass frequencies for the first-order stations, the predicted yearly frequencies, and the difference (predicted minus original) in frequencies.

The only differences between the original and predicted values occurred with the DT and T air masses. This is because of a documented problem with the SSC, where some extremely hot and dry days (high temperature and very low dew point), are mis-categorized as transition days instead of dry-tropical days (Sheridan

2000). This problem was accounted for in the neighborhood majority function and thus the discrepancy between the predicted values and the known values.

Table 3.3. Original known frequency values for first order stations as determined by the SSC (MS=missing data).

Summer air mass frequencies for first-order stations in or near study region for period of record (1948-2001).

Station	DM	DP	DT	MM	MP	MT	T	MS
Athens, GA	0.25	0.02	0.06	0.18	0.02	0.43	0.04	0.03
Atlanta, GA	0.26	0.03	0.03	0.23	0.02	0.39	0.06	
Birmingham, AL	0.25	0.03	0.03	0.20	0.01	0.45	0.04	
Charlotte, NC	0.22	0.04	0.08	0.19	0.02	0.42	0.04	
Columbia, SC	0.24	0.01	0.08	0.18	0.01	0.45	0.04	0.01
Columbus, GA	0.10		0.04	0.11		0.25	0.03	0.49
Greensboro, NC	0.24	0.05	0.07	0.22	0.02	0.37	0.04	0.01
Greenville, SC	0.24	0.04	0.06	0.20	0.02	0.40	0.04	0.03
Huntsville, AL	0.24	0.03	0.05	0.21	0.01	0.42	0.04	0.03
Jacksonville, FL	0.12		0.04	0.20		0.61	0.04	
Macon, GA	0.19	0.01	0.07	0.19	0.01	0.49	0.04	0.02
Meridian, MS	0.18		0.04	0.16		0.44	0.03	0.16
Mobile, AL	0.13		0.04	0.30		0.53	0.02	
Montgomery, AL	0.19	0.01	0.05	0.20		0.51	0.05	
Nashville, TN	0.19	0.04	0.03	0.16	0.01	0.46	0.04	0.10
Raleigh, NC	0.20	0.06	0.05	0.21	0.01	0.42	0.05	0.01
Savannah, GA	0.13		0.05	0.23	0.01	0.55	0.03	0.02
Tallahassee, FL	0.17		0.02	0.27		0.52	0.04	

Table 3.4. Same as Table 3.3 except summer air mass frequencies as calculated from neighborhood-majority function during cross validation procedure.

Interpolated summer air mass frequencies for first-order stations in or near study region for period of record (1948-2001).

Station	DM	DP	DT	MM	MP	MT	T	MS
Athens, GA	0.25	0.02	0.08	0.18	0.01	0.39	0.01	0.03
Atlanta, GA	0.24	0.02	0.05	0.22	0.02	0.35	0.01	
Birmingham, AL	0.25	0.02	0.05	0.20	0.01	0.40	0.01	
Charlotte, NC	0.23	0.04	0.09	0.20	0.02	0.36	0.01	
Columbia, SC	0.24	0.01	0.10	0.18	0.01	0.38	0.01	0.01
Columbus, GA	0.10		0.06	0.10		0.23		0.49
Greensboro, NC	0.24	0.05	0.08	0.22	0.02	0.32	0.01	0.01
Greenville, SC	0.24	0.04	0.07	0.20	0.02	0.37	0.01	0.03
Huntsville, AL	0.24	0.03	0.06	0.21	0.01	0.45	0.01	0.02
Jacksonville, FL	0.12	0.00	0.05	0.21		0.63	0.01	
Macon, GA	0.20	0.01	0.09	0.19	0.01	0.43		0.02
Meridian, MS	0.18		0.05	0.16		0.46	0.01	0.16
Mobile, AL	0.13		0.04	0.30		0.54	0.01	
Montgomery, AL	0.20	0.01	0.07	0.20		0.45	0.01	
Nashville, TN	0.18	0.04	0.04	0.16	0.01	0.48	0.01	0.10
Raleigh, NC	0.20	0.06	0.06	0.21	0.01	0.36	0.01	0.01
Savannah, GA	0.13		0.06	0.23	0.01	0.56	0.01	0.02
Tallahassee, FL	0.17		0.04	0.27		0.48	0.01	

Table 3.5. Difference between interpolated air mass values and known air mass values. A blank space indicates no difference.

Air mass frequencies differences for first-order stations in or near study region for period of record (1948-2001).

Station	DM	DP	DT	MM	MP	MT	T	MS
Athens, GA			0.01			-0.03	-0.03	
Atlanta, GA	-0.01		0.02	-0.01		-0.04	-0.05	
Birmingham, AL			0.01			-0.05	-0.04	
Charlotte, NC			0.01			-0.06	-0.03	
Columbia, SC			0.02			-0.07	-0.03	
Columbus, GA			0.02			-0.03	-0.03	
Greensboro, NC			0.01			-0.05	-0.03	
Greenville, SC			0.01			-0.03	-0.03	
Huntsville, AL			0.01			0.02	-0.04	
Jacksonville, FL			0.01			0.02	-0.03	
Macon, GA			0.02			-0.06	-0.03	
Meridian, MS			0.01			0.02	-0.03	
Mobile, AL						0.01	-0.01	
Montgomery, AL			0.02			-0.06	-0.04	
Nashville, TN			0.01			0.02	-0.03	
Raleigh, NC			0.01			-0.06	-0.04	
Savannah, GA			0.01			0.01	-0.02	
Tallahassee, FL			0.01			-0.03	-0.03	

3.5 Interpolating Cooperative Climatic Data to a Grid

As mentioned in the previous section there are two types of data that are interpolated to the grid of contiguous counties: air mass data and coop data. For the coop stations, it is important to interpolate the climate data to a grid over the entire contiguous-unit. If just one station is used, or if each station's records are analyzed individually, then localized land cover differences within a county group could bias the results.

The interpolation method is a DEM-aided interpolation as described in Wilmott and Matsura (1995). This method uses elevation data from a Digital Elevation Model (DEM) to determine differences in temperature as air cools at the environmental lapse rate. First, for all of the stations in each contiguous-unit the observation time of the data was verified to ensure that data from each station matched all of the other stations. Then the temperature for each station at sea level is determined using the following:

$$T_{SL} = T_O + 6.0 \cdot (H/1000) \tag{3.2}$$

where T_{SL} is the temperature of the station at sea level, T_O is the station's measured temperature, and H is the elevation in meters of the station. Next, Shepard's interpolation method (1968) is used to determine the sea level temperatures for each grid cell in the contiguous-unit. This interpolation is governed by the following equation:

$$T_{SL}(x, y) = \sum_{i=1}^{n} w_i f_i \tag{3.3}$$

where $T_{SL}(x,y)$ is the interpolated temperature at sea level with given latitude and longitude (x,y), n is the number of stations being used in the interpolation, w_i is the weighting function, and f_i is the temperature of each station i. The weighting function is governed by three equations:

$$w = \begin{cases} \dfrac{1}{d} & d < \dfrac{r}{3} \\ \dfrac{27}{4r}\left(\dfrac{d}{r} - 1\right)^2 & \dfrac{r}{3} \le d \le r \\ 0 & d > r \end{cases} \qquad (3.4)$$

where w is the weight used for each grid cell, d is the coop-station's distance from the grid point, and r is a specified search radius around the grid cell. In essence, if the station is close enough to the grid cell, a linear distance decay formula is used, if it is further away, a modified quadratic decay formula is used, and if the station is outside of the search radius, it is given a weight of zero. Finally, the interpolated temperature for the grid cell is determined by subtracting the product of the environmental lapse rate and the grid cell elevation from the interpolated sea-level temperature.

3.6 Estimating Dew Point Temperature

Dew point temperature, along with air temperature, is usually the most important variable when studying air mass character. The dew point temperature can relate is the dryness/moistness of an air mass, and therefore provides insight into the oppressiveness of an air mass more than only examining temperature, precipitation, or pressure. Coop stations normally do not record dew point temperature. However, daily minimum temperature has been shown to be a valid substitute for mean daily dew point temperature (Running et al., 1987; Glassy and Running, 1994)). Using this method, mean daily dew point temperature was estimated for each grid cell. This, along with maximum and minimum temperature, and daily precipitation are the variables that are available for analysis of air mass character over time in this study.

3.7 Determining Soil Moisture

Trees have root systems with which to tap moisture at depths below grasses or row crops in the Southeast. In theory, during dry periods that cause plant stress, trees should be able to add additional moisture to the atmosphere because of their ability to extract moisture from deep within the soil. The additional moisture input would be converted to latent energy that results in higher dew points and higher night-time air temperatures. The resulting differences in dew point depression would be especially noticeable during periods of high stress and in areas that have very high levels of forest cover compared to areas with very low levels of forest cover.

To test this hypothesis, daily soil moisture was estimated for eight county groups: Appling, GA; Barrow, GA; Choctaw, AL; Fairfield, SC; Iredell, NC; Jones, GA; Lee, GA and Morgan, AL. These county groups respectively have the highest and lowest forest cover levels through time and the most stable forest cover levels. In

addition, except for the county groups in Alabama, pairs of county groups with high and low forest cover can be easily compared because of the close spatial proximity (i.e. Appling compared to Lee, Jones compared to Barrow etc.).

Estimates of daily soil moisture were obtained using a soil moisture budget. This is based on the Thornthwaite model of soil moisture where the main source of soil moisture is precipitation and the main depletion sources are runoff and evapotranspiration. Daily potential evapotranspiration (PET) is estimated using the Thornthwaite (1948) empirical equation for monthly evapotranspiration:

$$ET_M = 1.6(10T_a / I)^a \qquad (3.5)$$

Where ET_M = monthly potential evapotranspiration, T_a is the monthly average temperature, I is the heat index value and a is a constant as given below.

$$I = \sum_{n=1}^{12} (0.2T_a)^{1.514}, \qquad T_a > 0^o C \qquad (3.6)$$

$$a = 6.75X10^{-7} I^3 - 7.71X10^{-5} I^2 + 1.7912X10^{-2} I + 0.49239 \qquad (3.7)$$

To convert monthly ET_M to a daily estimate (ET_D) a correction factor is used:

$$C = \frac{N}{360} \qquad (3.8)$$

where C is the correction factor and N is the hours of sunlight during the day (Snyder 2000).

In addition to the daily evapotranspiration, the available moisture holding capacity of the soil and the daily precipitation are also needed to determine soil moisture. The available moisture holding capacity is the difference between the field capacity of the soil and the wilting point throughout the entire root zone. This number varies depending on the soil type and the depth of the root zone. The available soil moisture is an instantaneous measure of the difference between field capacity and the wilting point. It is expressed in inches of water per inch of soil. In Table 3.6, ranges of available soil moisture for different soil types are given.

Table 3.6. Moisture capacity for soil types found in the study area (from Snyder 2000).

Soil Texture	Available Water Content (inches/inch)	Total Moisture Holding Capacity (assume 2ft. Rooting depth) (inches)
Sand	0.04 - 0.06	0.96 - 1.44
Loamy Sand	0.06 - 0.09	1.44 - 2.16
Sandy Loam	0.07 - 0.12	1.68 - 2.88
Loamy Sand	0.08 - 0.15	1.92 - 3.60
Clay Loam	0.10 - 0.18	2.40 - 4.32
Clay	0.12 - 0.21	2.88 - 5.04

Estimates of moisture holding capacity were determined using the State Soil Geographic Database (STATSGO) from the National Resource Conservation Service (NRCS). This is a spatial database that contains soil information that can be manipulated and viewed within a GIS. Using these data, the average available water content down to a two foot rooting depth was calculated for all soil types in the county group. These values were then weighted and averaged according to the percent of spatial coverage within the contiguous unit to calculate the total moisture holding capacity (at the 24 inch level).

The results for the 8 county groups are shown in Table 3.7. The clay soils of the Piedmont study area outside of the coastal plain result in higher AWC values compared to the two groups in the upper coastal plain that are predominated by sandy soils (Lee and Appling). The soils of these two groups would dry out faster than the other six. They are still used in this study because they are at similar latitudes, have similar climates, and are in opposing groups (e.g. Appling, GA is in a high forest cover group but Lee, GA is in a low forest group and both are in the coastal plain) that should effectively cancel out any bias they introduce.

Table 3.7. Available Water Capacity (AWC) and total moisture holding capacity (top 24" of soil) for the eight county groups used in the soil moisture analysis.

County Group	State	Forest Cover	AWC (in/in)	Moisture Holding Capacity (inches)
Appling	GA	High	0.09	2.1
Barrow	GA	Low	0.14	3.3
Choctaw	AL	High	0.13	3.0
Fairfield	SC	High	0.13	3.0
Iredell	NC	Low	0.14	3.3
Jones	GA	High	0.13	3.1
Lee	GA	Low	0.10	2.4
Morgan	AL	Low	0.14	3.4

3.8 Methodology Outline

This chapter outlined the procedure used to obtain and estimate yearly forest cover, daily air mass character, meteorological data, and soil moisture for spatially contiguous groups of counties. A graphical representation of the procedure is shown in Figure 3.13. Counties in the study area were clustered into three broad groupings (low, medium, and high forest cover) based on levels of forest cover through time. These large groups were then sub-divided into groups that were spatially contiguous and had similar levels of forest cover through time. They were then further sub-divided into contiguous counties that had data from at least three stations for 90% or more of the period of study (summers from 1948 – 2001). Two different interpolation methods were used to estimate daily summer air mass and meteorological values for these contiguous groups. Finally, the interpolated

meteorological variables were used to estimate soil moisture based on the Thornthwaite method. When complete, daily maximum and minimum temperature, daily dew point, daily precipitation, daily air mass value and character, daily soil moisture, and yearly forest cover are available for use in the final analysis.

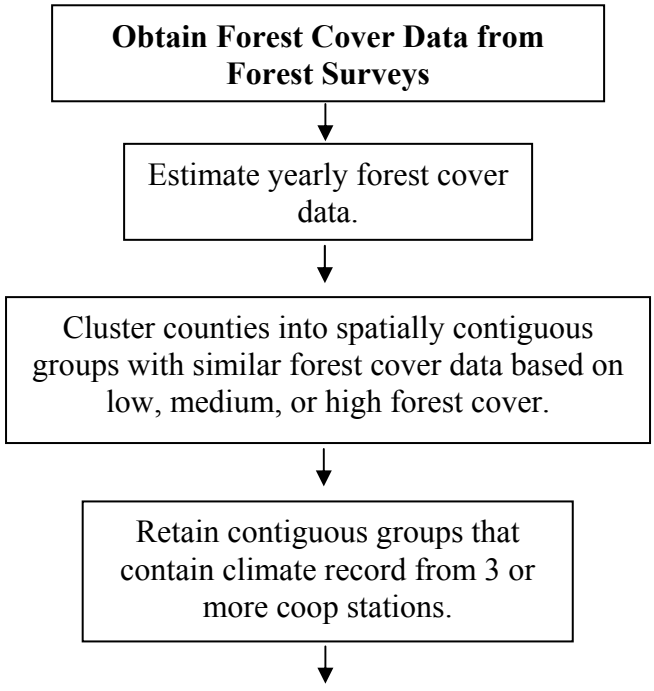

Figure 3.13. Procedure for estimating yearly forest cover and daily air mass character in this study.

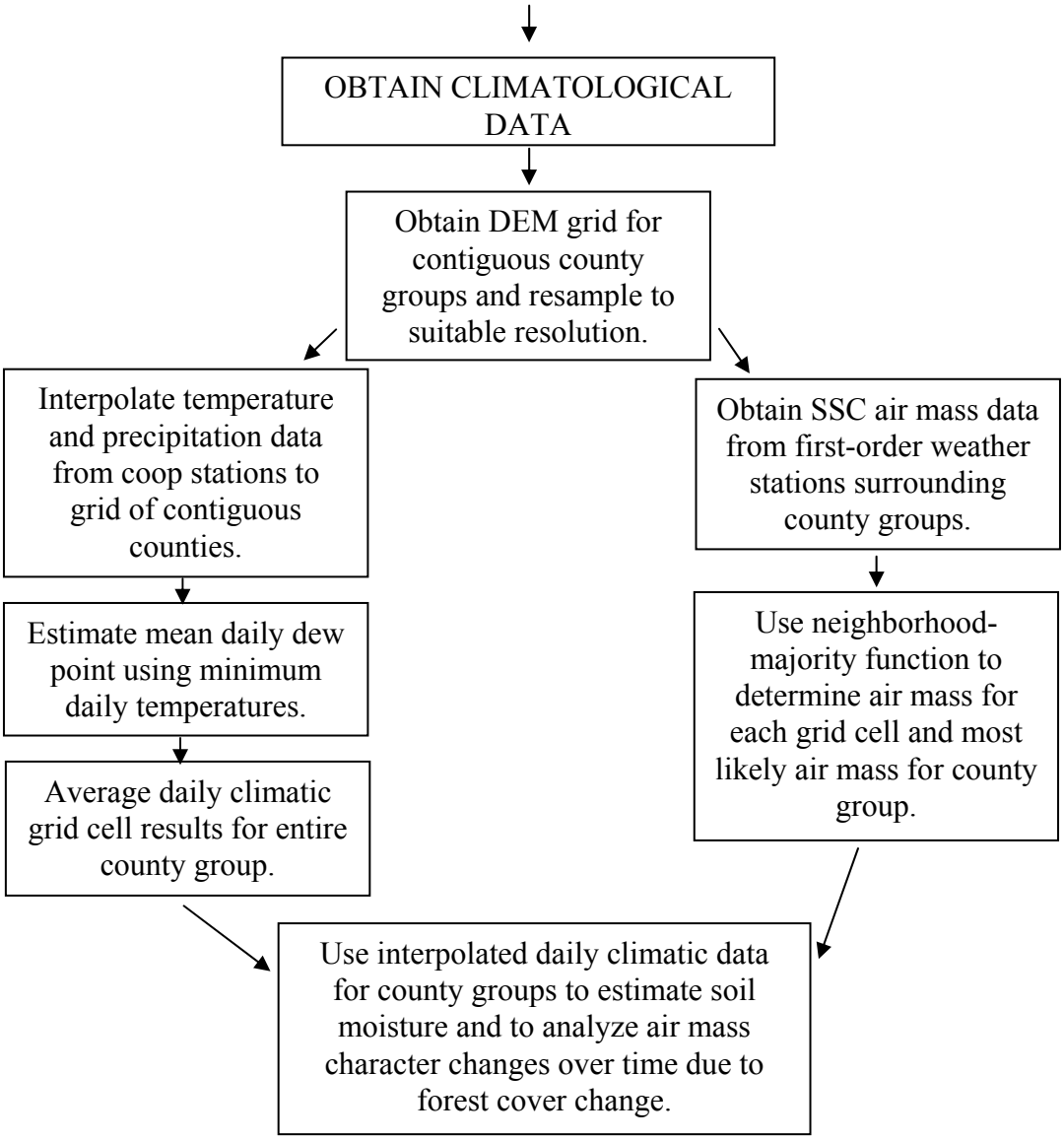

Figure 3.13. Continued.

Chapter 4

RESULTS

The procedures described in Chapter 3 produced 19 county groups for comparison between forest cover change and air mass character/climatological change (Figure 4.1). This chapter will discuss the results of the analysis of these data and the strength (or lack thereof) of the relationship between reforestation in the Piedmont and climate change. The first part of the chapter gives a spatial description of the county groups in terms of the clustered forest cover groups. The second part of the chapter presents the results of the air mass analysis and the daily temperature trends for the county groups. The third part shows the results of a multiple linear regression performed on the county groups in terms of mean forest cover, distance from the ocean, and several climate variables. The fourth section shows the results of a comparison of the variability in temperatures between the forest groups. The last part of the chapter deals with the results of an exploratory analysis of the water and energy balance at the surface.

4.1 Forest Cluster Characteristics

Three broad groups of contiguous counties were created based on forest cover through time using the clustering procedure outlined in the Methods chapter. Figure 4.1 shows all 19 county groups in terms of their respective clusters. Five county groups made up the low forest cover cluster (pink) and the medium forest

cover cluster (beige), and nine county groups made up the high forest cover cluster (green). See Appendix A for a list of all counties within each county group. The county groups are satisfactorily spread throughout the study region with low, medium, and high forest cover county units covering all parts of the Piedmont.

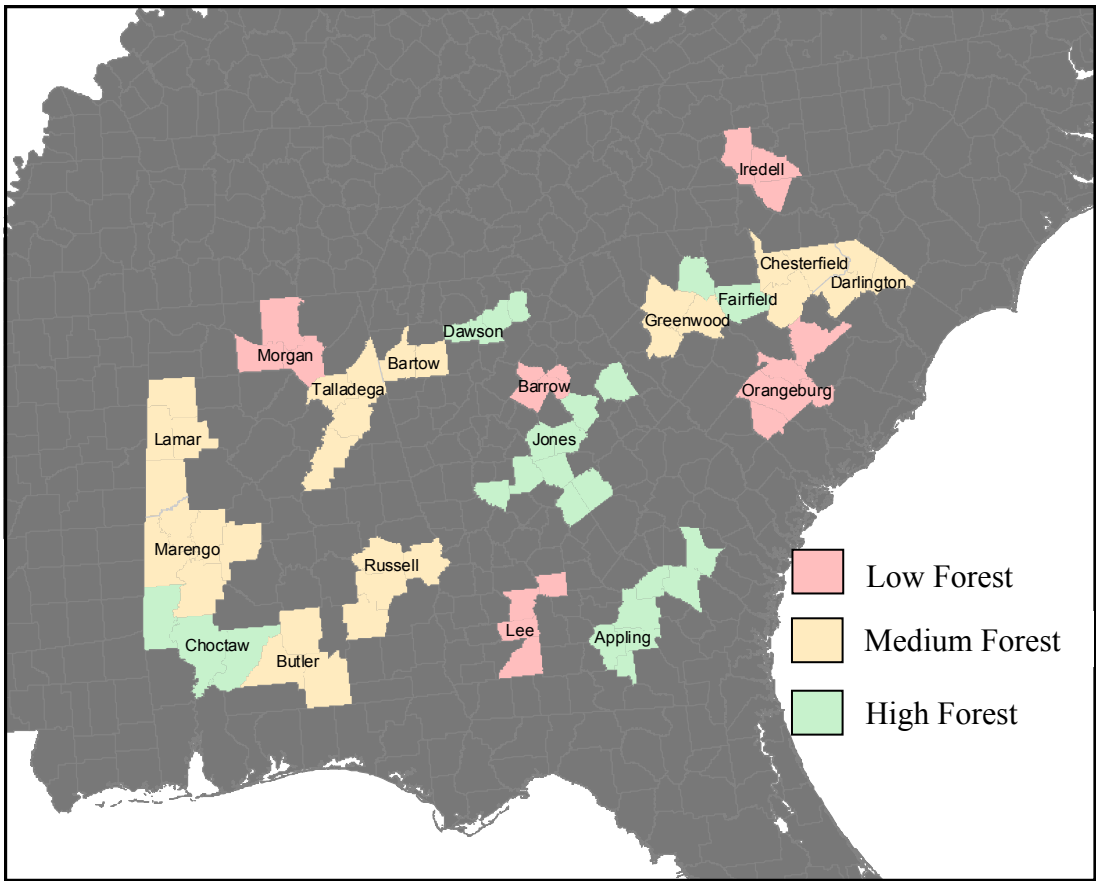

Figure 4.1. Location of county groups that were created from the methods described in Chapter 3.

For simplicity, each county group is named after one of the counties within that contiguous unit. Table 4.1 lists all of the county groups within each forest cover group. Following is a description of the forest cover trends for the three clusters.

Table 4.1. Names, number of counties, and area of contiguous county groups resulting from the clustering procedure outlined in Chapter 3.

Forest Cover Group	County Group Name	State	Counties In Group	Area (KM^2)
High	Choctaw	AL	3	8,231
High	Appling	GA	7	7,516
High	Dawson	GA	4	2,510
High	Jones	GA	9	9,055
High	Fairfield	SC	2	3,111
Total	**5**		**25**	**30,423**
Medium	Butler	AL	3	6,895
Medium	Lamar	AL	4	7,394
Medium	Marengo	AL	5	10,078
Medium	Russell	AL	4	6,599
Medium	Talladega	AL	4	6,309
Medium	Bartow	GA	2	2,517
Medium	Chesterfield	SC	4	5,372
Medium	Darlington	SC	4	3,745
Medium	Greenwood	SC	4	4,667
Total	**9**		**34**	**53,576**
Low	Morgan	AL	3	5,061
Low	Barrow	GA	4	2,067
Low	Lee	GA	4	3,812
Low	Iredell	NC	4	3,758
Low	Orangeburg	SC	4	6,563
Total	**5**		**19**	**21,261**

4.1.1 Low Forest Cover Cluster

The low forest cover cluster is composed of five county groups: Barrow, GA; Iredell, NC; Orangeburg, SC; Morgan, AL and Lee, GA. Three reasons account for the paucity of county groups in this cluster. The primary reason is the lack of suitable weather stations, which diminishes the available area that can be used in the analysis. In addition, using the standard deviation of yearly forest cover *for all counties* to place county groups into low, medium, or high clusters will necessarily result in fewer counties being placed into outlier groups. Consequently, more counties are placed in the middle forest cover group near the region-wide mean of each year's forest cover (see Chapter 3 for further explanation of the clustering procedure). Finally, by 1948 (the beginning of available air mass data for the SSC), most of the counties in the Piedmont already had forest cover levels above 50% of the total land area because of land abandonment in the preceding 30-50 years and resulting from reforestation on federal land purchased during the Depression. Notwithstanding this, there are still 18 counties in this cluster that cover 21,261 KM^2 with at least one county group located in each state.

Figure 4.2 shows that all of the low county groups experienced some level of reforestation during the period of study. The Morgan and Orangeburg groups had gradual reforestation (with initial forest cover of ~ 40%) during this period with the Orangeburg group eventually reaching forest cover levels near 60% of total land area. The Barrow and Iredell groups both experienced initial decades of growth followed by periods of decreasing levels of reforestation due to both increasing urbanization and timber harvesting. The final group, Lee County, had fairly constant levels of forest cover throughout the period of study. This is primarily an agricultural area and it has remained so during the last fifty years.

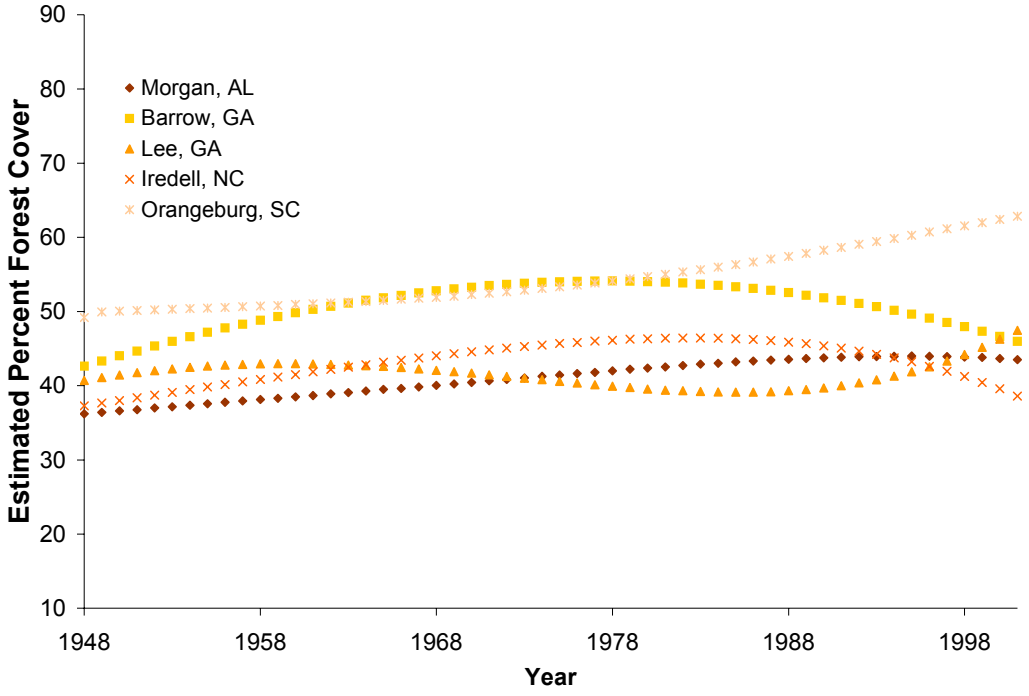

Figure 4.2. Estimated forest cover level as a percentage of total land area for the five county groups in the low forest cover cluster.

4.1.2 High Forest Cover Cluster

The high forest cover cluster also contains five county groups: Choctaw, AL; Appling, GA; Dawson, GA; Jones, GA and Fairfield, SC. For the entire high forest cover cluster, there are 25 counties covering a total of 30,423 KM^2. Once again there is good spatial coverage given the small number of county groups (Figure 4.1).

Most of the high forest cover counties experienced continued reforestation during the period of study (Figure 4.3). Only the Fairfield and Choctaw county

groups experienced reforestation for the entire 54-year period. The Appling county group experienced a rather precipitous decline in forest cover until the late 1980s when forest cover began to recover. The Jones County group had some initial increases in forest cover followed by generally stable levels of forest cover. The Dawson County group in the foothills of the Appalachian Mountains had some reforestation until the 1960s after which a slow decline in forest cover began due to timber harvests and an increasing human population.

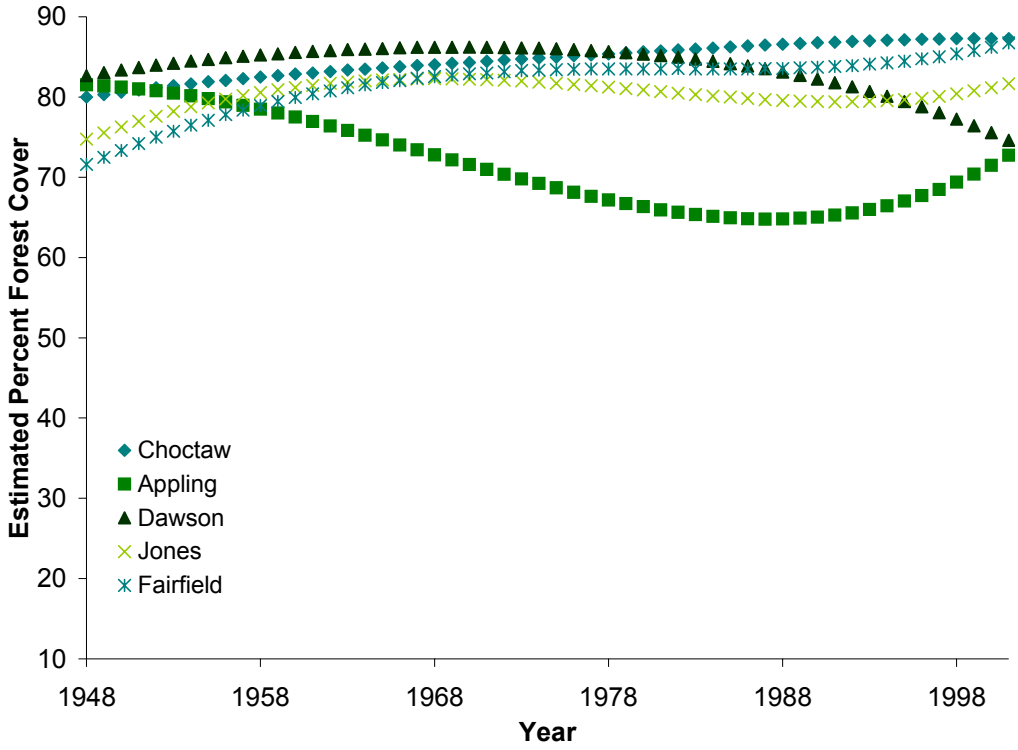

Figure 4.3. Estimated percent of land area in forest for each county group in the High Forest Cover cluster.

4.1.3 Medium Forest Cover Cluster

The medium forest cover cluster contains nine county groups: Butler, AL; Lamar, AL; Marengo, AL; Russell, AL; Talladega, AL; Bartow, GA; Chesterfield, SC; Darlington, SC and Greenwood, SC. This cluster is the largest because it contains all counties that are one standard deviation above or below the mean forest cover level of 1948 (see Chapter 3 for further explanation). The spatial coverage of this cluster is weighted towards Alabama (Figure 4.1). Five of the county groups are in this state while only one county group is in Georgia and three are in South Carolina. There is no particular spatial explanation for this distribution besides the fact that more county groups in Alabama had a sufficient number of climatological stations and therefore were not removed in the clustering and interpolation procedure.

The forest cover trends for the medium forest cover group fall into two categories as shown in Figure 4.4. The first of these categories (top graph) contains six county groups that experienced a general increase in percent forest cover throughout the period of study. The second category (bottom graph) consists of three county groups with more variability in the levels of forest cover. Two of the county groups in this second category experienced sinusoidal-type fluctuations in forest cover levels. These two groups, Talladega, and Bartow, are in a similar geographic location in northeastern Alabama and northwestern Georgia (Figure 4.1). This suggests similar land use patterns in this area and gives credence to both the clustering procedure and the Forest Service sampling technique that were employed in this research. The other county group, Greenwood, is in South Carolina and experienced reforestation for the first three to four decades followed by the beginning of a period of deforestation in the 1990s.

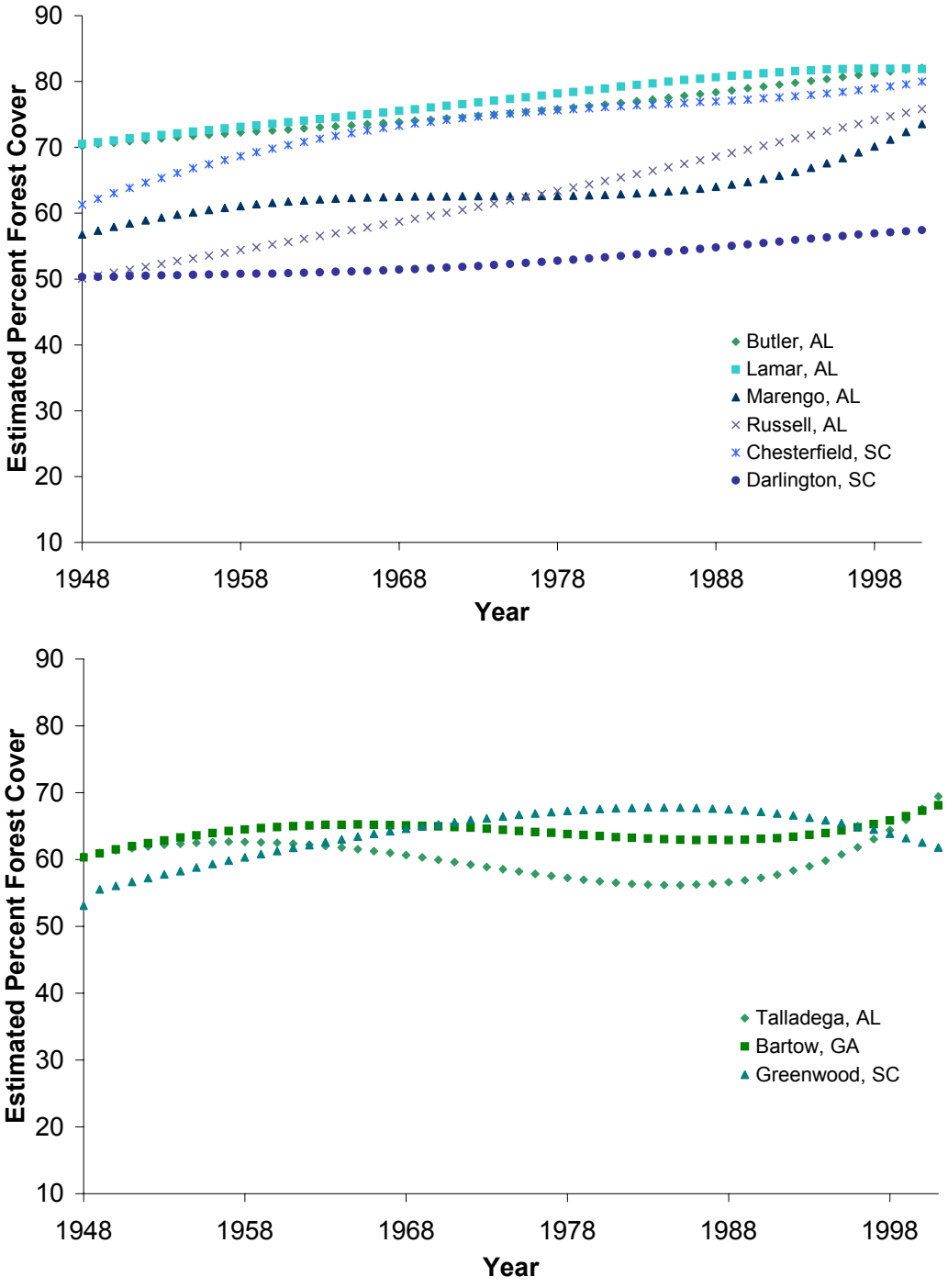

Figure 4.4. The two groups of forest cover levels for the medium forest cluster. There were nine groups in all for this forest cluster.

4.2 Air Mass Character

Of the seven air mass types produced by the SSC, only four are common during the summer months in the Piedmont. Dry Moderate (DM), Dry Tropical (DT), Moist Moderate (MM), and Moist Tropical (MT), all occur on more than five percent of days during the study period. The character of each of these air masses was examined for each county group and a summary of the character of these air masses follows.

4.2.1 Dry Moderate (DM)

As mentioned in Chapter 3, the Dry Moderate (DM) air mass is a warm dry air mass with no definite source region. Depending on the region of the study area, this air mass is either the second or third most-common air mass experienced. DM frequency tends to decline in the Piedmont as summer progresses and the MT air mass becomes dominant. DM frequencies drop to less than ten percent of all days along the coast to between ten and twenty percent in most of the contiguous county groups (Sheridan 2000).

Mean character for the DM air mass in the Piedmont has not changed substantially through the period of study. Table 4.2 shows the mean character for this air mass during three time periods of 18 years each. The mean minimum temperature value can also be interpreted as the mean daily dew point temperature as well (see chapter 3). The precipitation value is the percent of days with precipitation for that air mass.

Table 4.2. Dry Moderate air mass character for Piedmont county groups over three time intervals. The categories are mean maximum and minimum daily temperature, and the frequency of days experiencing precipitation.

Air Mass: DM	1948-1965				1966-1983				1984-2001			
County Group	% Forest	Max °C	Min °C	Precip Frequency	%Forest	Max °C	Min °C	Precip Frequency	%Forest	Max °C	Min °C	Precip Frequency
Low Forest Cover												
Morgan, AL	38	31	17	0.31	41	31	16	0.25	44	31	18	0.18
Barrow, GA	48	32	17	0.18	54	32	17	0.22	50	32	18	0.21
Lee, GA	42	33	20	0.47	41	32	19	0.27	42	33	20	0.26
Iredell, NC	40	30	17	0.25	45	31	17	0.24	44	31	17	0.32
Orangeburg, SC	51	33	18	0.37	53	32	18	0.36	59	33	19	0.38
Medium Forest Cover												
Butler, AL	72	32	18	0.42	75	32	18	0.38	80	32	18	0.34
Lamar, AL	73	32	16	0.29	77	31	15	0.28	81	32	16	0.24
Marengo, AL	60	33	19	0.33	62	32	18	0.31	66	32	19	0.28
Russell, AL	54	32	19	0.34	62	32	18	0.22	71	32	19	0.22
Talladega, AL	62	31	16	0.30	58	31	16	0.29	60	32	17	0.32
Bartow, GA	64	32	17	0.30	64	31	16	0.29	64	31	18	0.18
Chesterfield, SC	67	31	17	0.29	75	31	17	0.29	78	31	17	0.32
Darlington, SC	51	32	18	0.41	52	32	18	0.37	56	32	19	0.37
Greenwood, SC	62	32	18	0.31	71	32	17	0.23	69	32	18	0.31
High Forest Cover												
Choctaw, AL	82	32	18	0.34	85	32	17	0.34	87	32	19	0.36
Appling, GA	79	32	18	0.37	69	32	18	0.34	67	33	18	0.36
Dawson, GA	85	29	15	0.26	86	29	15	0.31	80	29	15	0.34
Jones, GA	79	32	17	0.26	82	32	18	0.27	80	32	18	0.21
Fairfield, SC	78	32	17	0.26	83	32	17	0.24	84	32	18	0.31

4.2.2 Dry Tropical (DT)

The Dry Tropical (DT) air mass is associated with the hottest and driest conditions. This is the least frequent of the four air masses commonly experienced in the Piedmont during the summer (generally less than ten percent of days). Table 4.3 shows the three 18-year averages for air mass character as in Table 4.2. Once again, no large noticeable trends in the character of the air mass are noticeable except for some large differences in precipitation. These large fluctuations are due to the small number of days in this air mass.

Table 4.3. Same as Table 4.2, except for the Dry Tropical air mass.

Air Mass: DT	1948-1965				1966-1983				1984-2001			
County Group	% Forest	Max °C	Min °C	Precip Frequency	%Forest	Max °C	Min °C	Precip Frequency	%Forest	Max °C	Min °C	Precip Frequency
Low Forest Cover												
Morgan, AL	38	36	19	0.23	41	36	19	0.11	44	37	22	0.15
Barrow, GA	48	35	19	0.21	54	36	21	0.23	50	36	21	0.29
Lee, GA	42	36	22	0.43	41	37	22	0.29	42	37	22	0.21
Iredell, NC	40	35	20	0.27	45	35	21	0.24	44	36	21	0.35
Orangeburg, SC	51	36	21	0.27	53	36	22	0.32	59	36	22	0.40
Medium Forest Cover												
Butler, AL	72	37	21	0.47	75	35	21	0.22	80	37	22	0.40
Lamar, AL	73	36	18	0.12	77	36	19	0.17	81	37	20	0.20
Marengo, AL	60	36	21	0.23	62	36	21	0.23	66	37	22	0.31
Russell, AL	54	36	21	0.19	62	36	21	0.18	71	37	23	0.17
Talladega, AL	62	36	18	0.25	58	36	20	0.37	60	36	20	0.27
Bartow, GA	64	35	18	0.27	64	35	20	0.24	64	36	22	0.15
Chesterfield, SC	67	35	20	0.39	75	36	21	0.23	78	35	20	0.34
Darlington, SC	51	36	21	0.46	52	36	22	0.34	56	36	22	0.46
Greenwood, SC	62	36	21	0.28	71	36	21	0.26	69	36	21	0.27
High Forest Cover												
Choctaw, AL	82	37	21	0.30	85	35	20	0.29	87	37	22	0.37
Appling, GA	79	35	21	0.22	69	36	21	0.29	67	37	22	0.33
Dawson, GA	85	32	16	0.33	86	33	18	0.27	80	33	18	0.39
Jones, GA	79	35	19	0.23	82	37	21	0.27	80	37	21	0.23
Fairfield, SC	78	36	20	0.23	83	36	21	0.21	84	36	21	0.31

4.2.3 Moist Moderate (MM)

The Moist Moderate (MM) air mass is associated with cool to warm moist conditions. In the Piedmont during the summer, this air mass is almost always associated with periods of clouds and rain and slightly cooler temperatures than normal because of the increased cloud cover. The frequency of occurrence of this air mass during the summer is generally between 15 and 20 percent of the days. MM air masses have the highest percentage of days with precipitation. For most of the county groups, between 85 and 98 percent of all days in this air mass experience some

precipitation. Table 4.4 shows the MM character for the county groups during the study period. Air temperature and dew point have remained relatively constant over time. The percentage of days with precipitation have fluctuated somewhat; most of the changes are decreases in precipitation frequency through time.

Table 4.4. Same as Table 4.2, except for the Moist Moderate air mass.

Air Mass: MM	1948-1965				1966-1983				1984-2001			
County Group	% Forest	Max °C	Min °C	Precip Frequency	%Forest	Max °C	Min °C	Precip Frequency	%Forest	Max °C	Min °C	Precip Frequency
Low Forest Cover												
Morgan, AL	38	30	19	0.91	41	30	19	0.89	44	29	20	0.84
Barrow, GA	48	29	19	0.94	54	29	20	0.91	50	30	20	0.94
Lee, GA	42	32	22	0.97	41	32	21	0.90	42	32	22	0.84
Iredell, NC	40	30	19	0.84	45	29	19	0.91	44	29	20	0.95
Orangeburg, SC	51	31	21	0.92	53	30	20	0.90	59	31	21	0.93
Medium Forest Cover												
Butler, AL	72	31	21	0.96	75	31	20	0.91	80	31	21	0.92
Lamar, AL	73	31	19	0.85	77	31	19	0.90	81	30	20	0.90
Marengo, AL	60	31	21	0.92	62	31	20	0.91	66	31	21	0.92
Russell, AL	54	31	21	0.93	62	31	20	0.88	71	31	21	0.87
Talladega, AL	62	30	20	0.96	58	30	19	0.98	60	30	20	0.98
Bartow, GA	64	30	19	0.92	64	29	19	0.90	64	30	20	0.79
Chesterfield, SC	67	31	20	0.92	75	30	20	0.89	78	30	20	0.90
Darlington, SC	51	31	21	0.94	52	31	20	0.90	56	31	21	0.93
Greenwood, SC	62	30	20	0.93	71	30	20	0.92	69	31	20	0.93
High Forest Cover												
Choctaw, AL	82	32	21	0.96	85	32	20	0.93	87	31	21	0.93
Appling, GA	79	31	21	0.96	69	31	20	0.95	67	32	21	0.95
Dawson, GA	85	27	17	0.90	86	27	17	0.88	80	27	18	0.91
Jones, GA	79	30	20	0.95	82	30	20	0.94	80	30	21	0.90
Fairfield, SC	78	30	20	0.87	83	30	20	0.91	84	30	20	0.94

4.2.4 Moist Tropical (MT)

The Most Tropical (MT) air mass is the most common air mass present over the Piedmont during the summer. Depending on the county group, between 40 and 55 percent of all summer days experience this type of air mass. With the Bermuda High well entrenched over the Atlantic, warm moist air is almost continually advected into the region. This air mass is responsible for the frequent afternoon convective thunderstorms that provide much of the summer precipitation for the Piedmont.

In Table 4.5 the mean character for the MT air mass shows that as with the other air masses, the character of the maximum and minimum temperature has remained the same when averaged over long time intervals. Likewise when the entire data set is examined for each county group, no consistent trend is found in the air mass character over time.

Interestingly, several county-groups saw declines in the average number of days with precipitation as measured over the three time periods. Some of this decline may be due to the fact that most of the missing days for the county groups with large decreases occur towards the end of the study period. Even accounting for this, it does appear that some decline in the amount of days with precipitation has taken place over the last 50 years. An examination of the Palmer Drought Index (PDI) values for the summer months did not reveal a strong relationship between the number of droughts in each time period and the decline in precipitation frequency (Table 4.6).

Table 4.5. Same as Table 4.2, except for the Moist Tropical air mass.

Air Mass: MT	1948-1965				1966-1983				1984-2001			
County Group	% Forest	Max °C	Min °C	Precip Frequency	%Forest	Max °C	Min °C	Precip Frequency	%Forest	Max °C	Min °C	Precip Frequency
Low Forest Cover												
Morgan, AL	38	33	20	0.67	41	32	20	0.63	44	32	20	0.47
Barrow, GA	48	32	20	0.66	54	33	20	0.59	50	33	21	0.72
Lee, GA	42	34	22	0.79	41	34	21	0.63	42	34	22	0.59
Iredell, NC	40	32	20	0.63	45	32	20	0.58	44	32	20	0.71
Orangeburg, SC	51	33	21	0.72	53	33	21	0.65	59	33	21	0.73
Medium Forest Cover												
Butler, AL	72	34	21	0.73	75	33	20	0.69	80	33	21	0.66
Lamar, AL	73	33	19	0.60	77	33	19	0.64	81	33	20	0.58
Marengo, AL	60	34	21	0.67	62	33	21	0.67	66	33	21	0.61
Russell, AL	54	34	21	0.65	62	33	21	0.56	71	33	21	0.53
Talladega, AL	62	33	20	0.73	58	33	20	0.72	60	33	20	0.73
Bartow, GA	64	32	19	0.80	64	32	19	0.64	64	31	20	0.53
Chesterfield, SC	67	33	20	0.70	75	32	20	0.62	78	32	20	0.65
Darlington, SC	51	33	21	0.77	52	33	21	0.68	56	33	21	0.73
Greenwood, SC	62	33	21	0.69	71	33	20	0.61	69	33	20	0.63
High Forest Cover												
Choctaw, AL	82	34	21	0.70	85	34	21	0.70	87	33	21	0.67
Appling, GA	79	34	21	0.74	69	34	21	0.69	67	34	21	0.74
Dawson, GA	85	30	17	0.72	86	30	18	0.67	80	30	18	0.71
Jones, GA	79	33	20	0.64	82	33	20	0.66	80	33	21	0.66
Fairfield, SC	78	33	20	0.63	83	33	20	0.62	84	33	21	0.67

Table 4.6. PDI drought value comparison with MT precipitation frequency. The table shows the total number of months for each time period that experienced PDI values below 0 (all air masses). This is presented in relation to the percent of days that experienced measurable precipitation for the MT air mass.

Air Mass: MT	Number of Summer Months with PDI < 0					
County Group	1948-1965		1966-1983		1984-2001	
Low Forest Cover	# Drought Months	Precip Frequency	# Drought Months	Precip Frequency	# Drought Months	Precip Frequency
Morgan, AL	33	0.67	19	0.63	29	0.47
Barrow, GA	28	0.66	21	0.59	23	0.72
Lee, GA	30	0.79	22	0.63	25	0.59
Iredell, NC	28	0.63	21	0.58	28	0.71
Orangeburg, SC	34	0.72	29	0.65	30	0.73
Medium Forest Cover						
Butler, AL	31	0.73	23	0.69	25	0.66
Lamar, AL	36	0.60	22	0.64	24	0.58
Marengo, AL	37	0.67	25	0.67	24	0.61
Russell, AL	37	0.65	25	0.56	24	0.53
Talladega, AL	34	0.73	18	0.72	27	0.73
Bartow, GA	34	0.80	22	0.64	27	0.53
Chesterfield, SC	35	0.70	23	0.62	31	0.65
Darlington, SC	28	0.77	20	0.68	30	0.73
Greenwood, SC	38	0.69	22	0.61	29	0.63
High Forest Cover						
Appling, GA	31	0.70	18	0.70	21	0.67
Choctaw, AL	31	0.74	23	0.69	25	0.74
Dawson, GA	28	0.72	21	0.67	23	0.71
Jones, GA	25	0.64	23	0.66	34	0.66
Fairfield, SC	25	0.63	23	0.62	31	0.67

The long-term averages of air mass character did not provide insight into the relationship between forest cover change and climate. Due to the inherent subtlety of any forest-climate relationships in contrast with the much stronger influences of the seasonal cycle, long-term averages will most likely mask any climate change. Finding any of these subtle effects requires an analysis of the data on different spatial and

temporal scales. It also requires different techniques to explore and analyze these data.

4.3 Temperature Trends

One way to explore these data on a different temporal scale is to visually examine all of the daily maximum and minimum temperatures for each county group to evaluate whether there are any statistically significant trends in the data. By observing the raw data, correlations between temperature changes and forest cover levels over time become apparent. A discussion of these trends follows.

To summarize the temperature trends the data were aggregated on a yearly timescale. The yearly data for each county group were tested using a linear regression model to see if the trends were statistically significantly different from zero (i.e. no change in temperature over time). The temperature data trends were evaluated to see if there were any large changes over time and to see if forest cover level was correlated with temperature. The correlation coefficient (Pearson's r), the slope of the line, and the significance of the relationship were computed for each county group. The results, summarized in Appendix B on Tables B.1 through B.3, indicate that at this spatial scale (i.e. for individual county groups) the strength of the relationship between forest cover level and temperature is weak at best. Out of the 38 tests to evaluate the correlation between forest cover and temperature (19 county groups times 2 climate variables), only 11 yielded results that indicated the slopes were significantly different from 0 ($p < 0.1$). Of the 11 tests that were statistically significant, seven showed a negative correlation between forest cover and temperature while four indicated a positive relationship. Therefore, these contradictory results do not imply that there is a strong relationship between forest cover and temperature. The

only strong trend is an increase in minimum temperatures over time. Even here though, only 8 out of 19 county groups had statistically significant ($p < 0.1$) positive trends over time.

The lack of a clear trend over time is also evident when the daily temperature data are examined. Charts of the maximum and minimum daily air temperatures with the calculated linear trends are also presented in Appendix B. These daily temperatures are the gridded interpolated temperatures that were calculated using the methods described in Chapter 3.

The maximum and minimum daily temperatures during the period of study for the low forest cover cluster are displayed in Figure B.1. No strong linear trend is evident in these data by themselves. For the minimum daily air temperature, there may be a slight upward trend over the period of study. If this were the case, then it would also indicate an increase in the mean daily dew point temperature. This is because in humid climates minimum daily temperature can be substituted for the mean daily dew point temperature (see Chapter 3). Overall, no significant trends are evident from linear regression analysis. There may indeed be correlations in these data with forest cover, but if there are, the climatological noise blocked out these relationships in this portion of the analysis.[1]

Maximum daily air temperatures in the high forest cluster did not consistently trend one way or the other (Figure B.2). The Jones and Appling County groups had slight upward trends in temperature, and the Choctaw County group had a slight downward trend. For the minimum daily air temperature (and mean daily dew

[1] A more in-depth analysis of the temperature and precipitation data was conducted using evapotranspiration and soil moisture estimates. The discussion of these results is located in the last part of the chapter.

point temperature), the Jones County group noticeably trended upward over time while the Fairfield and Choctaw County groups trended upward after initial decreases in temperature. But once again, a simple review of the data did not produce any significant correlations between forest cover through time and daily temperature or mean dew point temperature.

Figure B.3 shows the maximum and minimum daily temperatures over the period of study for the nine county groups in the medium forest cover cluster. No discernable trend is apparent for the maximum daily temperatures. For minimum daily temperatures, two county groups, Lamar and Talladega (both in northern Alabama) had upward trends in minimum daily temperature while the data in the other seven county groups were inconclusive. Even the discernable positive linear trends in Lamar and Talladega county groups were weak and cannot be linked to forest cover level at this very basic level of analysis.

Overall, simple examinations of the data with fitted linear trend-lines were not successful in discovering meaningful results. There is too much noise in the data within each county group. These data are useful in showing that any impact of reforestation on climate is subtle and is not readily apparent by simply examining the climate record by itself. These data also illustrate that the clustering and interpolation procedures developed for this study were successful. The clustering procedure created spatially valid groups with similar forest cover and the interpolation procedure produced a useable gridded climatology of the groups over the entire area.

4.4 Effect of Geographic Location on Air Mass Character

As an alternative to examining each county group individually or in pairs, all groups were combined together in a regression analysis of the mean of these data.

This type of analysis was chosen because statistics about the mean should be helpful in interpretation of forest cover's impact on climate and as a data reduction technique. Through regression analysis, multiple factors such as distance from the ocean and elevation as well as forest cover were used to determine the relative contribution of each to the total variability found in all of the climatic means.

Linear regression analyses were performed with the climatic data stratified by air mass using the statistical analysis extension within Microsoft Excel™. Forest cover, distance from the ocean, and elevation above sea level were used as the independent variables. Many other factors could have been tested as well, such as seasonality or soil type. These three were chosen because it was assumed that most of the variability due to frontal passages was removed because the study period is restricted to the summer months. In addition, it was hypothesized that distance from the ocean and elevation would be the most influential factors determining variability in the mean of the climate variables.

For every county group, the climate variable in question was divided into five-year increments. The mean of the variable was calculated for each increment and used in the regression analysis. In addition, the analysis was performed for each combination of dominant air mass (DM, DT, MM, MT) and climatic variable. The precipitation data was calculated in a slightly different manner that resulted in the average number of days in a ten-day period with precipitation over the five-year period for each air mass.

The results of the regression tests are summarized in Tables 4.7 and 4.8 (complete results are found in Appendix C). The tests did indeed show that distance from the ocean and elevation were both important factors in the variability of the mean

of the climatic variables. In general the model explained much of the variance for maximum and minimum temperatures and almost none of the variance in the precipitation data (Table 4.8). Forest cover was an important factor but the link is tenuous when the results are viewed graphically.

Figure 4.5 illustrates this point. Here, the mean daily maximum temperature is plotted versus percent forest cover for the Dry Moderate air mass. Notice the large range of temperature values (~6 ^{o}C) regardless of the level of forest cover. The 'significance' and large R^2 value (0.51) returned by the regression analysis is likely the result of the relatively large sample size (188 mean temperatures), the slight negative trend in the temperature data, and one outlying county group that places undue influence on the outcome of the test.

Table 4.7. Summary of regression analysis results for four dominant Piedmont summer air masses.

Independent Variable Dependent Variable	**Forest Cover** Significant Results by Air Mass	**Distance** Significant Results by Air Mass	**Elevation** Significant Results by Air Mass
Minimum Temperature (Mean Daily Dew Point)	DM, DT, MM, MT	DM, DT, MM, MT	DM, DT, MM, MT
Maximum Daily Temperature	DM, DT, MM, MT	None	DM, DT, MM, MT
Total Precipitation	DM, DT, MM, MT	MM, MT	MM, MT

Table 4.8. Adjusted R^2 values for multiple linear regression for all climate variables tested according to air mass type.

Climate Variable	R^2 by Air Mass Type			
	DM	DT	MM	MT
Maximum Temperature	0.51	0.29	0.66	0.64
Minimum Temperature	0.51	0.54	0.74	0.72
Precipitation	0.17	0.02	0.07	0.14

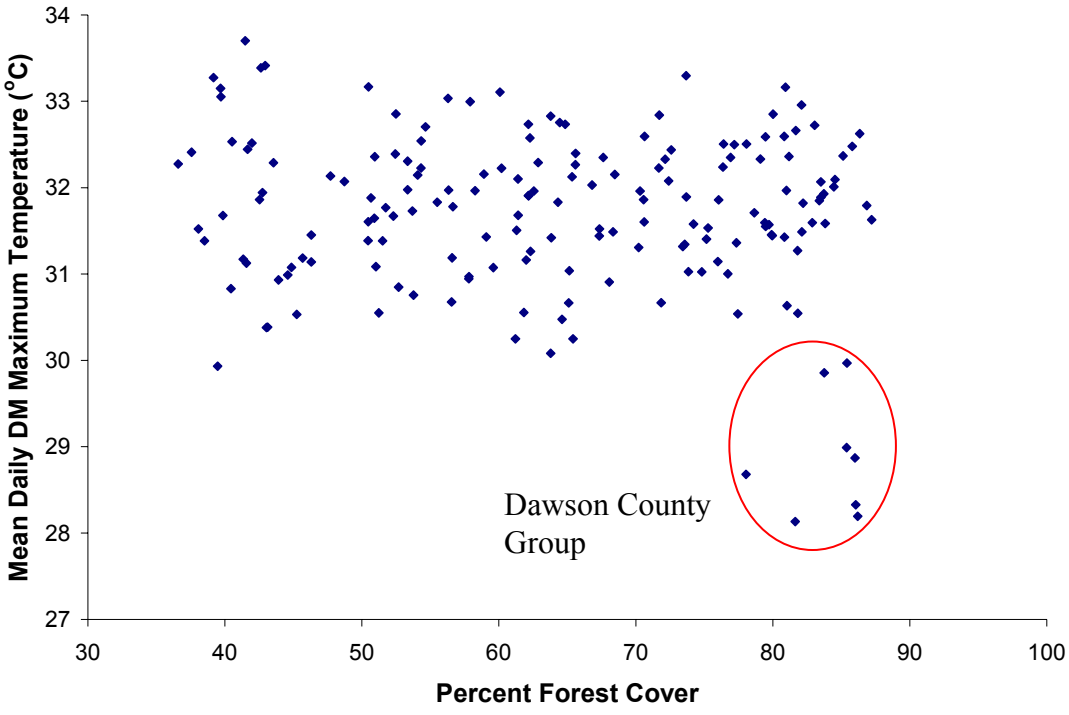

Figure 4.5. Maximum temperature vs. percent forest cover for all county groups during days with the DM air mass.

The temperatures from the outlier group in Figure 4.5 (circled in red) belong to the Dawson county group. The anomalous data from this county group are primarily due to Dawson County's location in the foothills of far northern Georgia. It's very high forest cover level placed it at the extreme high end of the forest cover range and led to the spurious results seen with this test. The other two independent variables in the regression test (distance from the ocean and elevation) had much stronger trends and are more likely to explain the variance in the data than were used in this portion of the analysis. The r^2 results from the regression analysis without the Dawson County group are presented in Table 4.9 (and in Appendix C) for comparison. Notice how much less of the variance is explained once the Dawson County Group is removed.

Table 4.9. Same as Table 4.8 except for the removal of the Dawson, GA county group from the regression analysis.

	R^2 by Air Mass Type			
Climate Variable	DM	DT	MM	MT
Maximum Temperature	0.21	0.11	0.49	0.34
Minimum Temperature	0.37	0.41	0.56	0.56
Precipitation	0.18	0.02	0.07	0.20

4.5 Air Mass Character Variability

The Coefficient of Variability (CV) was calculated for every 20-day period from 1948 – 2001 for each county group (see Appendix D for an explanation of this variable) to test if the variability between county groups differed because of forest cover levels. Calculations were made for maximum and minimum daily temperatures. Comparisons were then made between every county group for each dominant summer air mass. This resulted in a total of 2,652 total comparisons (221 county pair comparisons X 4 air masses X 3 climate variables). In each county comparison, the CV values were calculated by subtracting the CV values of one county group from the other county group.

The results of the comparisons were inconclusive. For every divergent forest cover pair that had consistent differences in variability another forest cover pair could be found that had the exact opposite pattern of differences in CV values. A slightly different method of employing the CV is described in the soil moisture analysis section of this chapter.

4.6 Moisture Analysis

The estimated daily percent soil moisture (SM) and daily precipitation were used as the basis to test paired data groupings for statistically significant differences in climate due to forest cover. Two of the county groups were removed from the low forest cover group (LFCG) and high forest cover group (HFCG) before the data were pooled. The Dawson, GA group was removed from the high forest cluster because its location in the foothills introduced too much elevation bias as seen in the regression analysis. The Orangeburg, SC group was removed from the low cluster because its forest cover was higher than the rest of the LFCG's.

The remaining county groups were combined into one LFCG and one HFCG. Gamma functions were estimated from the grouped data for each test and then compared for significant differences using the Kolmogorov-Smirnov Categorical Difference Test (KS Test, see Appendix D). Means-based parametric statistical tests were not appropriate to compare results because all of these distributions are non-normal gamma distributions.[2]

A description of each of the comparisons follows:

1. **Precipitation** – Comparison of daily station data (not interpolated precipitation data) for measurable precipitation events (i.e. greater than trace amounts of precipitation).

2. **Consecutive days below 35% soil moisture** – The difference in the amount of consecutive stress days (days with soil moisture less than 35% of field capacity). For example, in the combined LFCG there were 55 instances of the stress period lasting only one day, 16 instances of it lasting five days, and six instances of it lasting ten days.

3. **Size of precipitation event to end stress period** – The magnitude of the single precipitation event that caused the soil moisture to increase above the 35% level. In effect this is the rain event that "broke" a period of soil moisture stress.

4. **Amount of precipitation between stress periods and consecutive days between stress periods** – These are two comparisons resulting from the same test. After a county group emerges from a stress period, how many days were there before the next stress period and during this time how much precipitation fell? For example in the LFCG there were 30 instances where only one day occurred between stress periods and there were 14 instances where eight days occurred between stress periods.

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[2] Chi-square tests were performed for all frequency distributions to compare observed frequencies to expected (normal) frequencies. The p-values for all distributions were much less than 0.001 indicating that all the distributions were significantly different from the expected normal distribution.

5. **Amount of precipitation to reach 50% SM and days to reach 50% SM** – Once again, these are two comparisons derived from the same test. That is, once the county group enters into a stress period, how long does it take for it to reach 50% SM, and how much precipitation did it require to reach this percentage? The individual precipitation event (as opposed to the cumulative precipitation) that increased soil moisture above 50% SM is also compared to the individual precipitation event that increased soil moisture above 35% SM (test 3).

6. **Overall sensitivity of precipitation to SM** - The distribution of precipitation events are compared during periods when SM is less than 35%, 35 to 50%, 50 to 75% and greater than 75% of field capacity.

7. **Probability of precipitation** - Test to determine if the probability of receiving any precipitation is different between the two groups.

The results showed that for the tests described above, none showed significant differences at the 0.01 or 0.1 alpha levels (Table 4.10). Some of the results did point to slightly drier conditions for the LFCG. However, the differences were very small and the results may have important implications for the way GCMs model land cover change's effects on the hydrologic cycle.

Table 4.10. Summary of results of the analysis of the effects of forest cover on soil moisture and precipitation.

Test	Significant at 0.01 level?	Significant at 0.1 level?	Result of Test
Precipitation Event Size	No	No	Low Forest Cover Group slightly drier
Consecutive Days Below 35% SM	No	No	Both groups very similar to each other
Size of "Drought" Ending Precipitation Event(s)	No	No	Slightly larger precipitation events raised SM above 35% in Low Forest Cover Group
Amount of Precipitation Between Stress Periods	No	No	Slightly less precipitation between stress periods in Low Forest Cover Gorup
Amount of Precipitation to Reach 50% SM	No	No	Low Forest Cover Group had slightly more precipitation to raise SM above 50%

4.6.1 Precipitation Events

The precipitation event comparison showed that the LFCG was slightly drier than the HFCG but not at a statistically significant level. The KS-test calculated a maximum D value of 0.04 which is not significant at the 0.1 alpha level (critical D = 0.19, N = 40). An inspection of the probability curves in Figure 4.6 reveals that a greater percentage of the precipitation events for the LFCG were comprised of smaller amounts of precipitation (< 20mm). But again, the negligible differences mean that the null hypothesis (i.e. forest cover does not impact precipitation) cannot be rejected.[3]

A visual comparison of the histograms of the raw data in Figure 4.7 magnifies the differences in precipitation. The histogram is split into 1 mm bins for the first 10 precipitation events, 5 mm bins for precipitation events up to 60 mm and 10 mm bins for the remainder of events. The greatest differences are in the first three or four bins where the LFCG has higher probabilities of small precipitation events. The 5 mm bins show the switch to higher probabilities of larger precipitation events in the HFCG.

[3] The effect of the geographic location of the county groups on precipitation was tested to ensure the validity of these results. See Appendix E for further details.

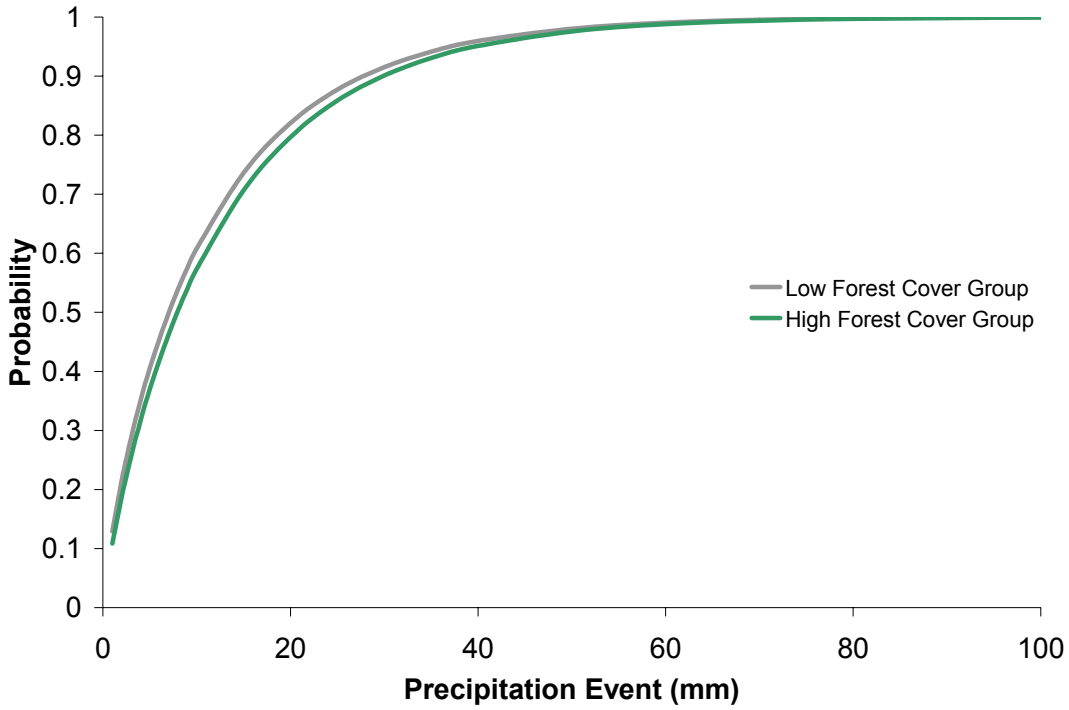


Figure 4.6. Estimated gamma functions of 24 hour precipitation probability for the HFCG and LFCG.

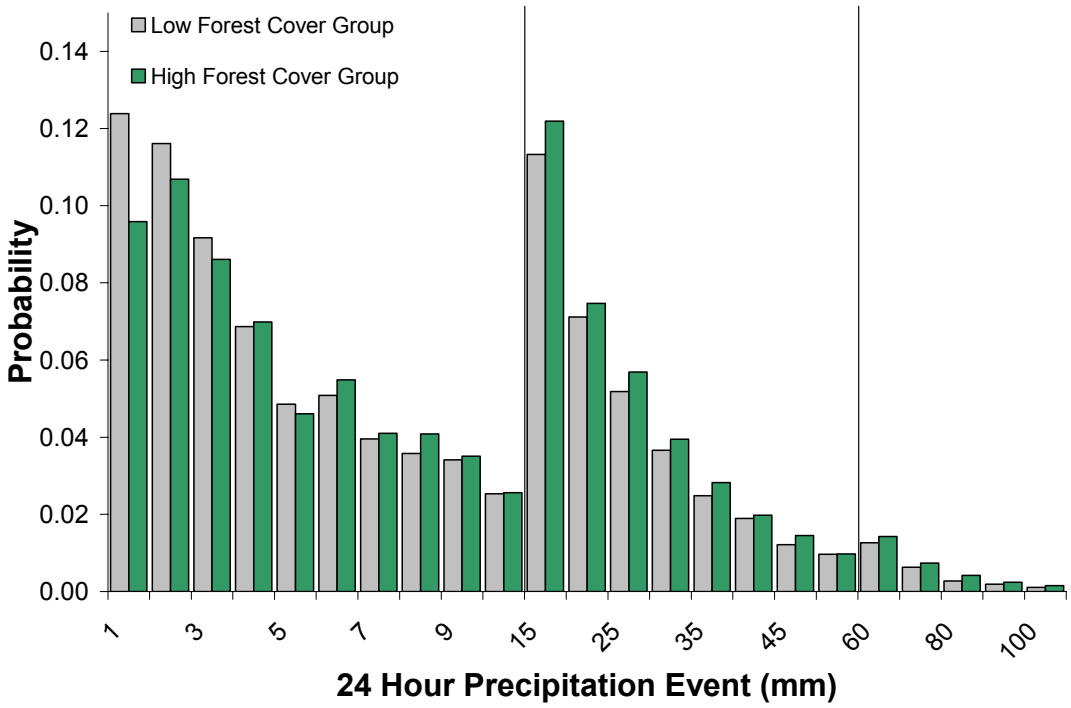


Figure 4.7. Histogram comparison of precipitation probabilities (from raw station data) for the LFCG and HFCG. Dividers indicate transition from 1 mm to 5 mm to 10 mm bin sizes.

4.6.2 Stress Periods Length

Comparison 2 tests for differences in the number of consecutive stress days (< 35% SM). In Figure 4.8 the gamma curves are almost identical and the results accordingly were not statistically significant (D = 0.00, critical D = 0.23 at $\alpha = 0.01$, critical D = 0.17 at $\alpha = 0.1$). Little consistent variation can be seen between the two groups. For instance in the histogram shown in Figure 4.9, in three of the first five bins (which describe short stress periods) the LFCG has higher probabilities of occurrence for those stress period lengths than the HFCG; however only two of the

next five bins show higher probabilities for the LFCG. Overall, the two groups are too similar to conclude that forest cover plays a role in influencing the length of a stress period.

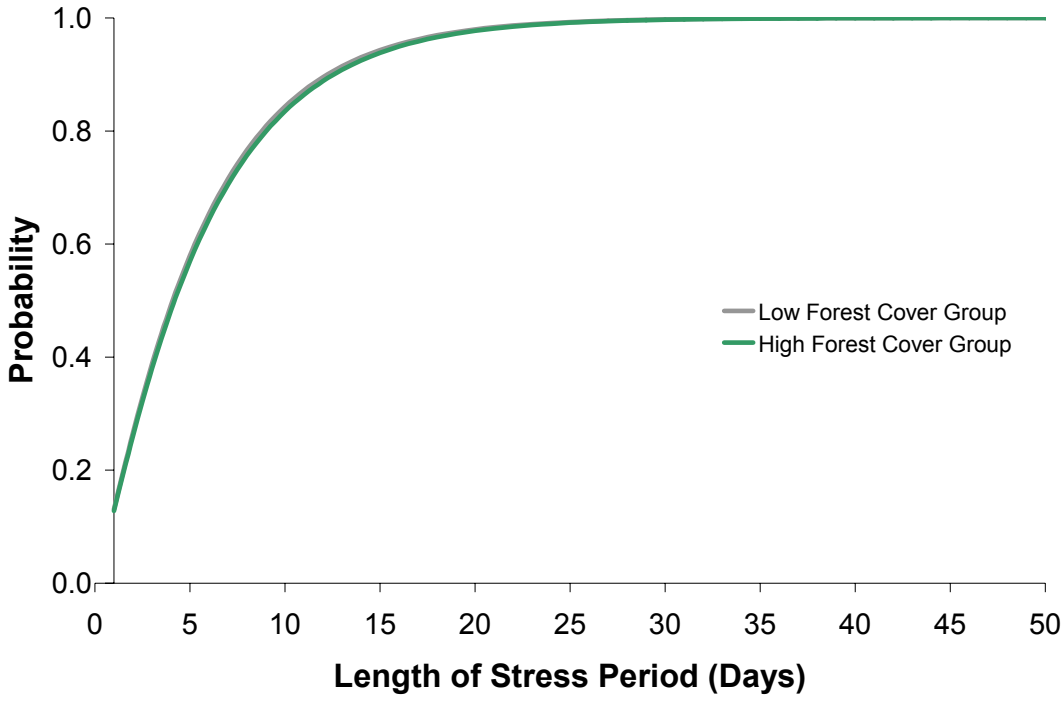


Figure 4.8. Estimated gamma function depicting probability of consecutive days within a stress period.

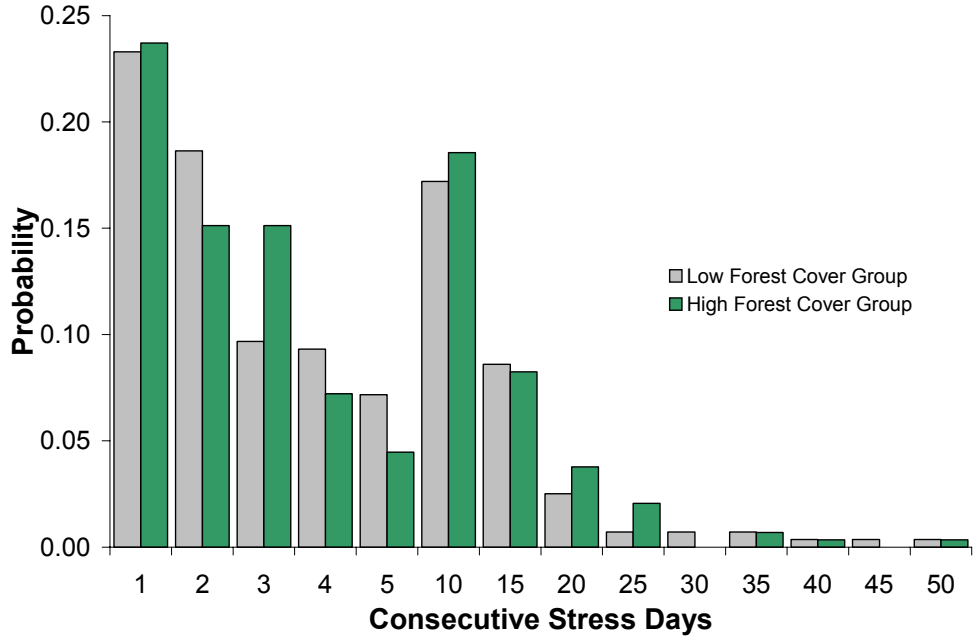


Figure 4.9. Histogram comparison of number of days in a stress period. Data are from actual probabilities (i.e. not from estimated gamma function).

4.6.3 Precipitation During Stress Periods

Comparison 3 analyzed the size of the precipitation event that raised soil moisture above 35% of the field capacity (Figure 4.10). The KS-test of the estimated gamma function indicated the two forest cover groups were not significantly different from each other ($D = 0.10$, critical $D = 0.21$ at $\alpha = 0.1$). While this test did show the greatest difference between the two groups, it is too small to conclude that forest cover is influencing the precipitation regime during vegetative stress periods.[4]

[4] See Appendix E for a discussion of the effect of field capacity on the results of this test.

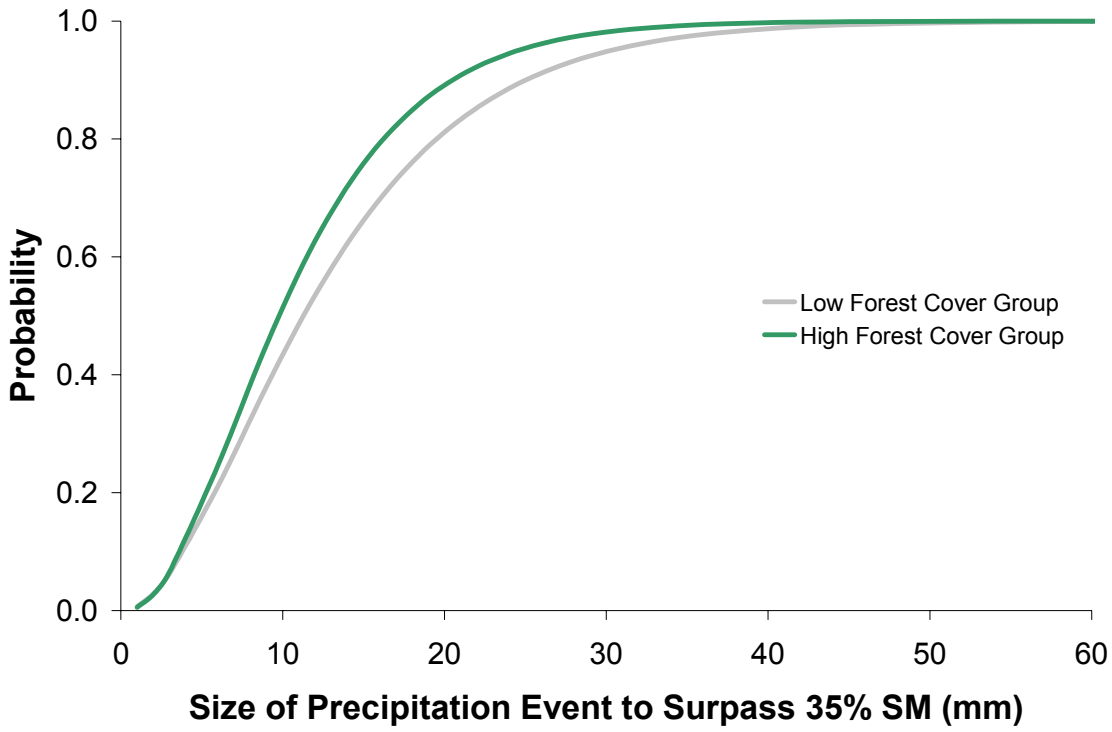


Figure 4.10. Distribution of size of precipitation event to surpass 35% SM during a stress period.

The differences in how precipitation fell during the stress periods were also compared. The probability of precipitation events during stress periods is shown in Figure 4.11. No significant differences were found between the two groups ($D = 0.00$, critical $D = 0.17$ at $\alpha = 0.1$). In fact, the estimated gamma functions are almost identical. Similarly, the comparison between the cumulative amount of precipitation that fell during each stress period (Figure 4.12) for the two groups shows no significant differences ($D = 0.03$, critical $D = 0.19$ at $\alpha = 0.1$).

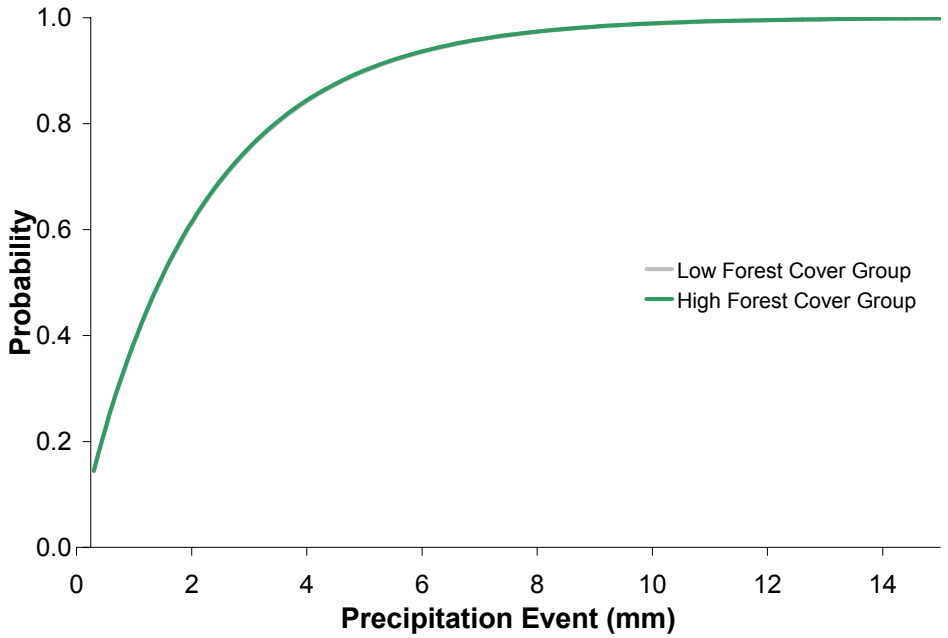


Figure 4.11. Size of precipitation event during stress periods (< 35% SM).

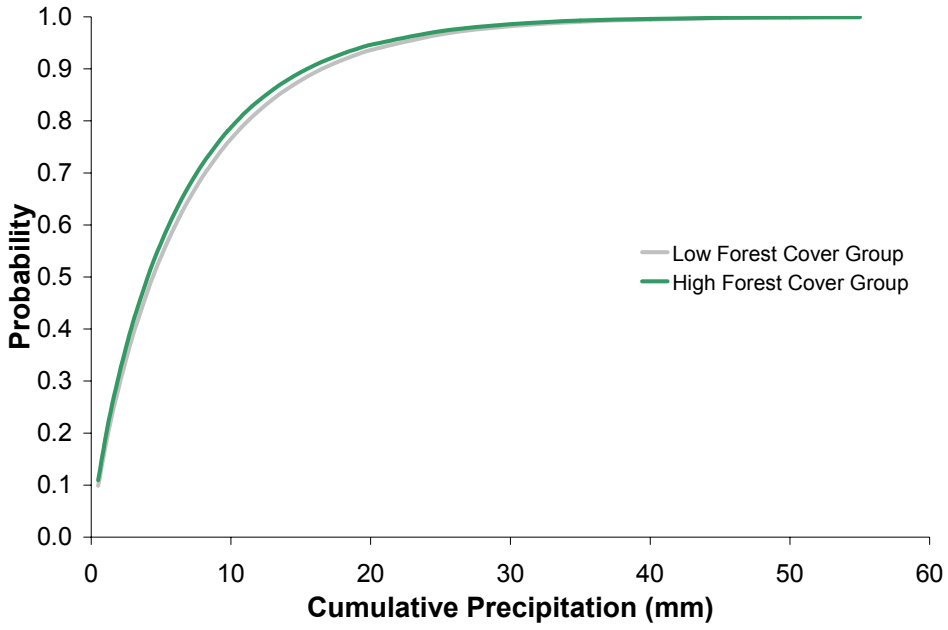
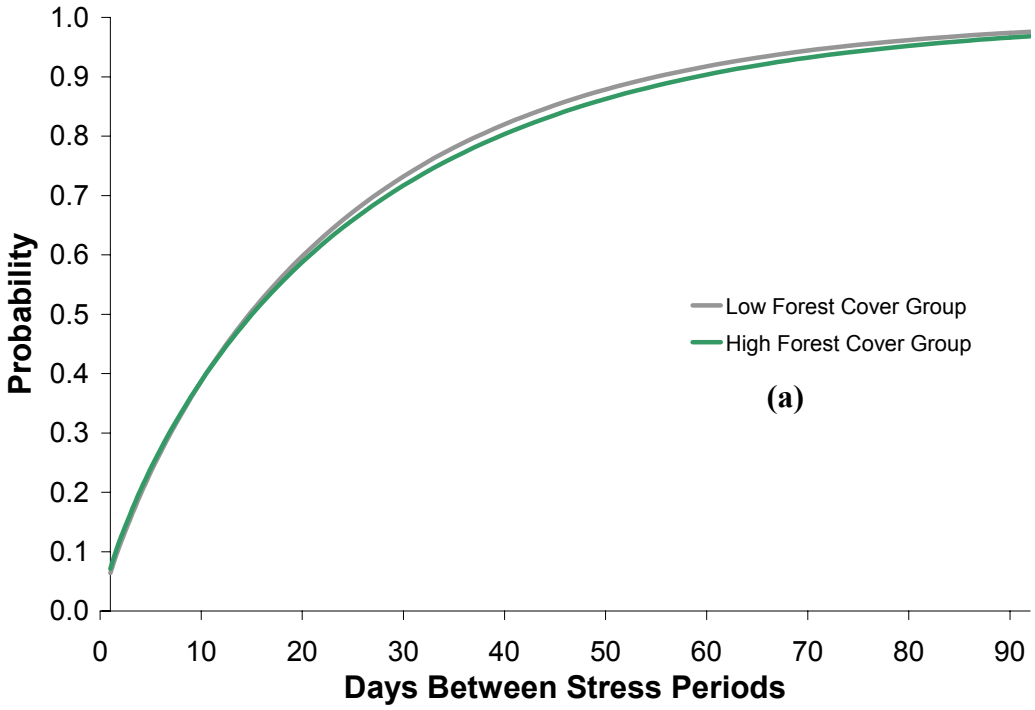
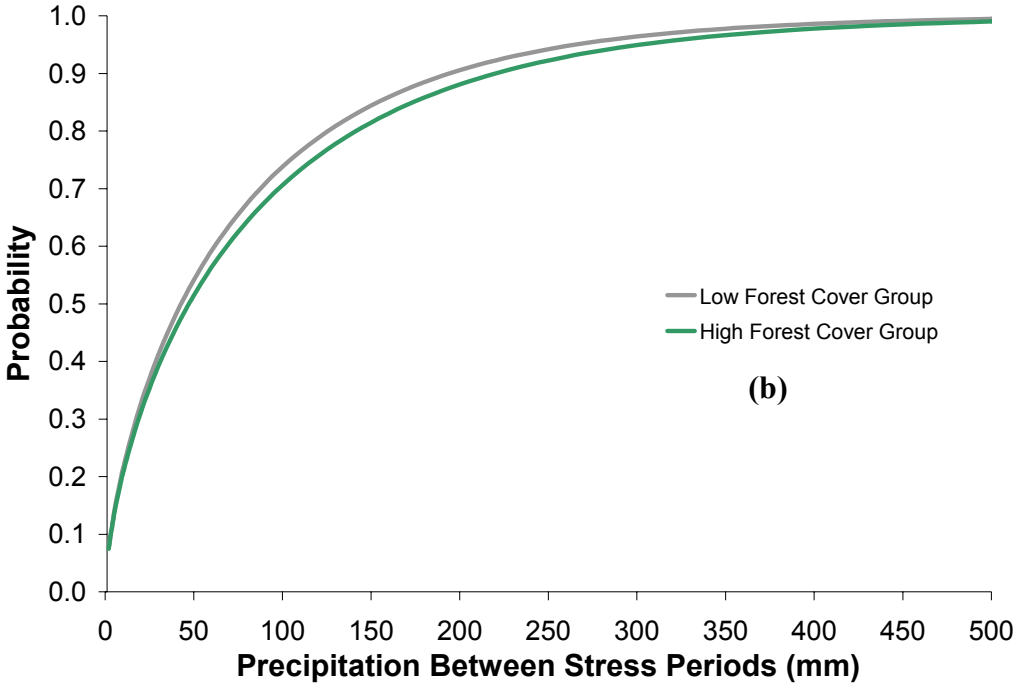


Figure 4.12. Probability of total amount of precipitation during a stress period (< 35% SM).

4.6.4 Non-Stress Periods

The fourth comparison of the two groups tested the difference between the number of days and the amount of precipitation between stress periods (i.e. non-stress periods). As in the previous comparisons, the number of days between stress periods was not statistically different between the two groups (Figure 4.13a, D = 0.02, critical D = 0.15). Likewise the difference in precipitation amounts between the two groups was not statistically significant at the 0.1 alpha level (Figure 4.13b, D = 0.03, critical D = 0.15). The probability curves in Figure 4.13a and b suggest that the HFCG experienced slightly more precipitation and slightly longer interludes between stress periods. But the differences are too small to make statistical inferences about differences in the populations.

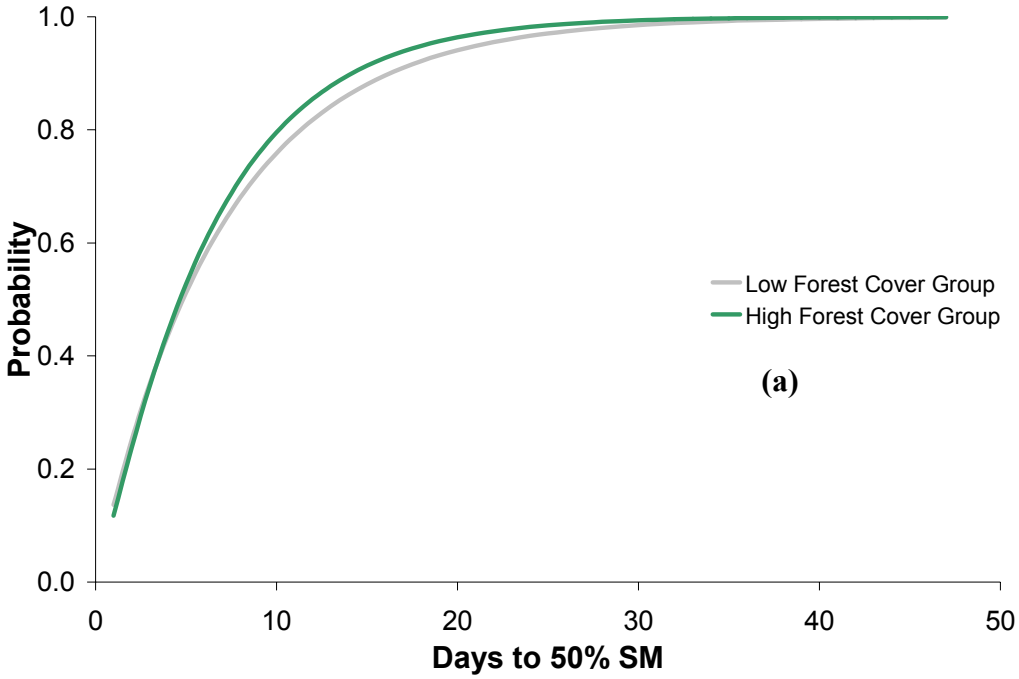




Figures 4.13a and 4.13b. Length of time (a) and cumulative precipitation (b) between stress periods (35% or less soil moisture values).

4.6.5 50% SM Comparison

The fifth comparison tested the differences in the length of time and the amount of precipitation needed to reach a threshold of 50% soil moisture (Figure 4.14a and 4.14b). Once again, the HFCG's length of time to reach 50% soil moisture was not significantly different from the LFCG (D=0.04, critical D=0.18 at $\alpha = 0.1$). And again, the difference in cumulative precipitation to reach 50% SM was not significantly different between the two groups (D = 0.09, critical D = 0.18 at $\alpha = 0.1$).



Figures 4.14a and 4.14b. Probability of time and cumulative amount of precipitation needed after the end of a stress period to reach 50% SM.

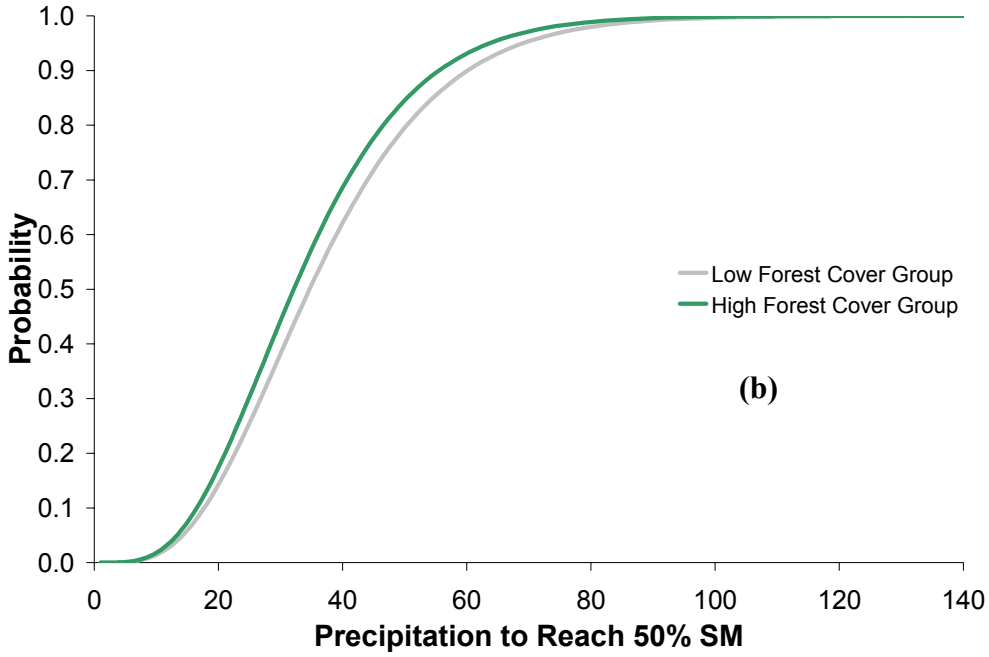


Figure 4.14. Cont'd.

The size of the precipitation event to surpass 50% SM was also tested (Figure 4.15). The results were almost identical to those in Test 3. The differences between the two groups were slightly larger than in the other tests (D = 0.10, critical D = 0.21 at $\alpha = 0.1$) but still not statistically significant. The fact that the distribution is very similar to that shown in Figure 4.10 indicates that soil moisture does not have an impact on the size of the precipitation event (only the reverse holds true). This test and the probability curves shown in Figures 4.14a and b demonstrate that this comparison is consistent with the previous results indicating that the impact of forest cover on the hydrologic cycle is minimal or non-existent in these two groups.

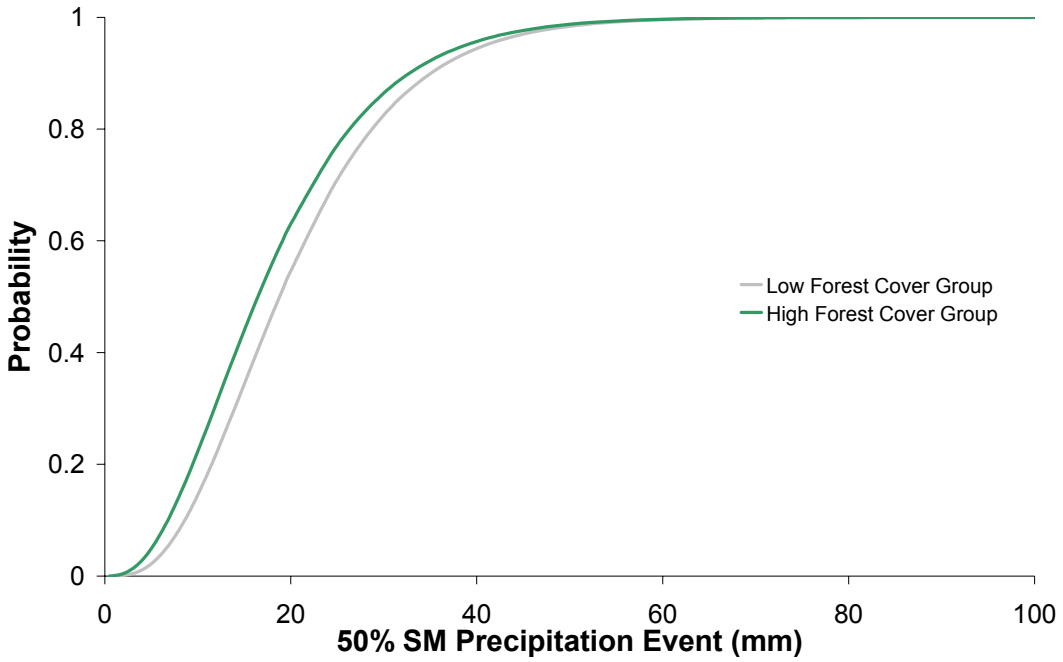


Figure 4.15. Probability of size of precipitation event to surpass 50% SM.

4.6.6 Probability of Precipitation

The sixth comparison looks at the probability of precipitation under several soil moisture conditions. The conditions examined were soil moisture levels of less than 35%, 35 to 50%, 50 to 75%, and more than 75% of field capacity.5 The results are presented in Figure 4.16. Recall, that these probabilities are derived from interpolated precipitation values averaged over a grid of the county group. As such, they only reflect the probabilities of 'average' amounts of precipitation in a county group.

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[5] The gamma function curve of precipitation events with less than 35% SM is the same as shown in Test 3.

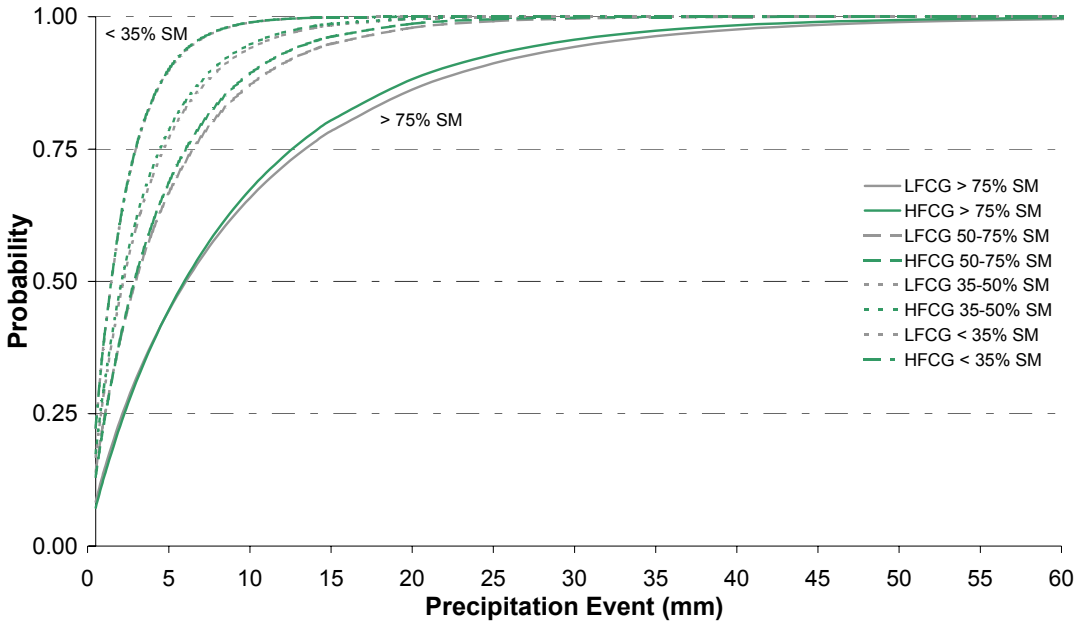


Figure 4.16. Probability of precipitation events over four soil moisture intervals: < 35% SM, 35-50% SM, 50-75% SM, and > 75% SM.

The data show that, as expected, periods of soil moisture deficiency are concurrent with small rain events and vice versa for periods with high soil moisture. More importantly, these data show that forest cover does not affect precipitation amounts. None of these probability curves show significant differences between the LFCG and the HFCG ($D < 0.28$, $\alpha = 0.1$). Although it appears that the differences between the groups increase as the soil moisture increases, even these (non-significant) differences are likely due to the increasing variance of the data. Table 4.11 illustrates this by showing that high soil moisture indicates periods of more frequent and larger precipitation events than if the soil moisture is low. Thus, the standard deviation of precipitation events will be higher as the number of precipitation events

increases and the range of the size of those events increases. Therefore, small differences between the LFCG and the HFCG will become slightly larger as soil moisture increases.

Table 4.11. Standard deviation of precipitation events over the four soil moisture intervals.

	Standard Deviation	
Percent SM	LFCG	HFCG
< 35	2.3	2.3
35 - 50	3.7	3.4
50 - 75	5.2	4.5
> 75	11.0	10.1

The final comparison tests whether the probability of receiving precipitation (PoP) differs between the two groups. The raw station data were used in this test (as opposed to the interpolated station data), because of the large errors that interpolation of discrete precipitation data introduces when calculating the overall PoP. Using interpolated precipitation values is justified in several of the previous tests because only the distribution of precipitation and precipitation events were examined. In addition, because it was necessary to aggregate forest cover data across multiple counties, soil moisture could only be calculated using interpolated precipitation data. Thus, to be consistent only interpolated precipitation data are used when soil moisture is the variable in question. When it is not (either by choice or necessity), station data are used.

A chi-square test was used to test for significant differences between PoP for the HFCG and LFCG. The frequency table and results of the test are given in Table 4.12. The test showed no significant differences between the two groups PoP (Chi-square value = 0.213, P-value = 0.645). This and every previous test show that for this study area's time and place, forest cover does not significantly affect the probability of precipitation or the size of the precipitation event.

Table 4.12. Frequency of precipitation events (P), and Chi-square test of expected differences between the HFCG and LFCG.

Frequencies	NoP	P	N	PoP
HFCG	86,339	37,623	123,962	0.3035
LFCG	67,948	29,482	97,430	0.3026
Chi-square	0.213			
P-value	0.645			

4.7 Soil Moisture Impact on Temperature

Soil moisture and diurnal temperature range (DTR) were used to examine the effect of forest cover on air temperature. The diurnal temperature range was chosen as opposed to maximum or minimum temperature because it is a function of the local energy balance and it was hypothesized that low soil moisture contributes to higher maximum temperatures and lower minimum temperatures (i.e. conditions

experienced during hot and dry periods). This is a more appropriate comparison than solely examining maximum or minimum temperature since DTR is the better measure of the energy balance and because high maximum temperatures can occur in isolation with or without moist conditions in the Southeast. In addition, low soil moisture is an indication of drought which is usually accompanied by large DTRs. Using the DTR also allows for direct comparison between spatially diverse groups since maximum and minimum temperatures will vary by region, but the range of temperatures in the study area is assumed to be relatively consistent during the summer months.

The comparisons were structured in a similar way to the precipitation tests. The same HFCG and LFCG were used as in the precipitation analysis. Five comparisons were created depicting temperature response to drought and soil moisture changes:

1. **Overall Relationship between soil moisture and DTR** – Do the HFCG's and the LFCG's correlations between soil moisture and DTR differ?

2. **Average temperature range to end of stress period** – During a stress period, what is the average DTR?

3. **Frequency of daily temperature ranges experienced during all stress periods -** This is the frequency of temperature ranges as the days within a stress period increase.

4. **Frequency of daily temperature ranges experienced for varying stress periods** – Similar to the previous test except that the data are divided into five-day bins to explore any differences between the groups with regards to the DTR as the length of stress period changes.

5. **Temperature range to 50% SM –** The frequency of DTRs once a stress period begins until the soil moisture reaches 50%.

4.7.1 Soil Moisture and DTR

Before examining what occurs during specific soil moisture conditions, it is useful to first observe the general relationship between soil moisture and the DTR. In Table 4.13 the frequency count of daily DTR are displayed for the LFCG and HFCG. These tables show how the DTR decreases as soil moisture increases. This corresponds to the hypothesis stated above that drier conditions correspond to higher daytime and lower nighttime temperatures. The most common values center around a combination of a DTR of 12.5 ^{o}C and soil moisture between 60 and 70% of field capacity.

Table 4.14 shows the differences between the LFCG and HFCG. Each frequency count in Table 4.13 was converted to a percentage of the total number of days (14,886 and 16,815 days for the LFCG and HFCG, respectively). The difference between each corresponding frequency percent was then calculated to create the table. Gray areas (and positive values) are where the LFCG had a higher percentage of days with that combination of DTR and soil moisture range. Green areas (and negative values) show the opposite situation. This table establishes that the LFCG had lower DTRs than the HFCG. The mean DTR differences are confirmed with a student's t-test (Table 4.15).

Table 4.13. Frequency of DTRs for a given range of soil moisture values for the LFCG (top) and HFCG (bottom).

Low Forest Cover Group

Diurnal Range (°C)		2.5	5	7.5	10	12.5	15	17.5	20	22.5	All
	10	0	0	0	0	4	11	6	0	0	21
	20	0	1	5	29	126	167	65	5	0	398
	30	0	4	24	123	395	410	120	12	1	1089
	40	0	9	53	223	656	643	164	20	1	1769
% SM	*50*	1	9	74	306	862	663	158	17	2	2092
	60	5	21	122	497	964	584	104	14	0	2311
	70	4	31	137	510	991	485	104	5	0	2267
	80	2	32	151	593	825	333	59	7	0	2002
	90	4	34	161	514	643	186	42	3	0	1587
	100	20	74	306	544	345	58	3	0	0	1350
	All	36	215	1033	3339	5811	3540	825	83	4	14886

High Forest Cover Group

Diurnal Range (°C)		2.5	5	7.5	10	12.5	15	17.5	20	22.5	All
	10	0	0	0	1	2	11	6	3	0	23
	20	0	0	1	16	72	238	105	10	0	442
	30	0	1	11	56	284	570	225	26	3	1176
	40	0	3	25	138	640	814	183	17	0	1820
% SM	*50*	0	8	40	276	993	871	179	9	2	2378
	60	0	11	59	363	1189	742	97	17	0	2478
	70	3	15	82	424	1202	576	89	9	0	2400
	80	1	20	97	536	1085	423	63	2	0	2227
	90	3	20	112	575	892	294	29	6	0	1931
	100	8	87	346	769	630	96	4	0	0	1940
	All	15	165	773	3154	6989	4635	980	99	5	16815

Table 4.14. Difference in percent of days for a diurnal range/soil moisture combination between the LFCG and HFCG. Gray shaded areas indicate a higher percentage of days for the LFCG at that diurnal range/soil moisture combination and vice versa for green areas.

(LFCG %Total) - (HFCG %Total)

Diurnal Range (°C)		2.5	5	7.5	10	12.5	15	17.5	20	22.5
	10									
	20				0.1	0.4	-0.3	-0.2		
	30			0.1	0.5	1.0	-0.6	-0.5	-0.1	
	40			0.2	0.7	0.6	-0.5			
% SM	*50*			0.3	0.4	-0.1	-0.7		0.1	
	60		0.1	0.5	1.2	-0.6	-0.5	0.8		
	70		0.1	0.4	0.9	-0.5	-0.2	0.2		
	80		0.1	0.4	0.8	-0.9	-0.3			
	90		0.1	0.4		-1.0	-0.5	0.1		
	100	0.1			-0.9	-1.4	-0.2			

Table 4.15. Summary statistics and student's T-test results comparing difference of means in DTR for the HFCG and LFCG.

Statistic	Mean	Standard Deviation	Median
HFCG	12.7	2.4	12.90
LFCG	12.4	2.6	12.50
T-Test			
T-Value	13.4		
p-Value	0.000		

The relationship between DTR and soil moisture is examined further in Figure 4.17. A linear regression line for the DTR is plotted against the estimated soil moisture. There is a noticeable increase in the DTR as the soil moisture decreases (about 0.5 ^{o}C for every 10% decrease in SM). And again from this figure, it appears that the LFCG has smaller DTRs than the HFCG. This is not because one particular county group is acting as an outlier as seen in Table 4.16 and Figure 4.18. The correlation coefficients, slope, and r^2 values for the eight county groups show that the LFCG consistently has lower DTRs while the HFCG has slightly steeper slope values and a stronger correlation with soil moisture levels.

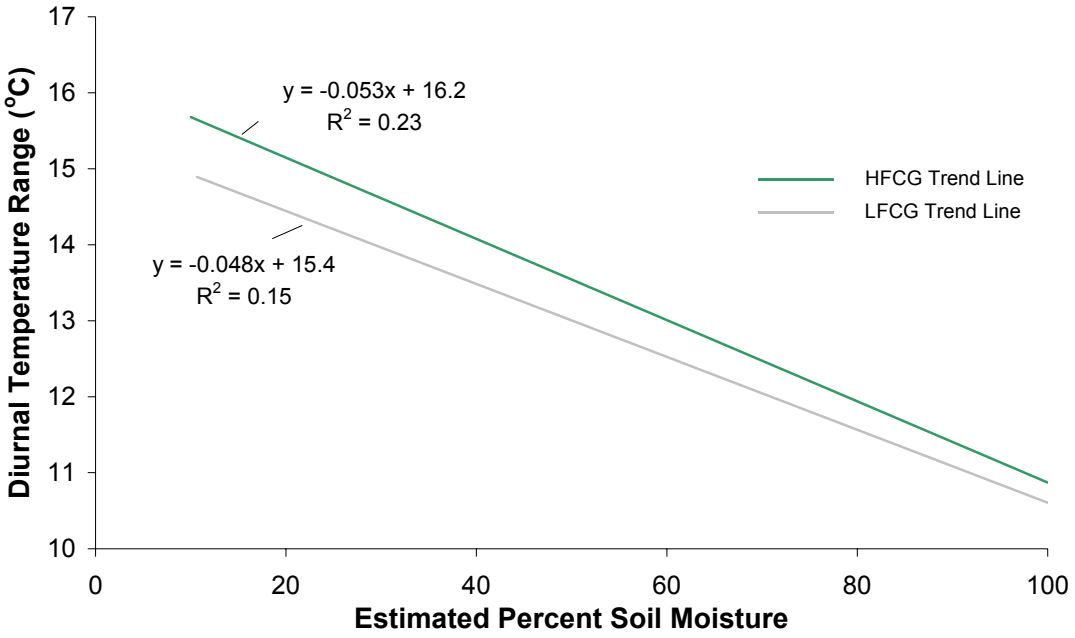


Figure 4.17. Linear trend line of DTR associated with changes in soil moisture. The statistics for the two fitted lines are given in Table 4.14.

Table 4.16. Correlation and linear regression results when comparing DTR to percent soil moisture. The last column estimates the value of the trend line through each county group when the soil moisture equals 100%.

County Group	r^2	r	Slope	Intercept	X at 100% SM
Appling	0.28	-0.53	-0.05	16.0	11.1
Choctaw	0.24	-0.49	-0.05	16.3	11.0
Fairfield	0.21	-0.45	-0.06	16.4	10.7
Jones	0.26	-0.51	-0.06	16.3	10.6
Barrow, GA	0.21	-0.46	-0.05	15.4	10.1
Iredell, NC	0.11	-0.33	-0.05	15.8	11.0
Lee, GA	0.22	-0.47	-0.05	15.0	10.4
Morgan, AL	0.17	-0.42	-0.06	16.1	10.6
Combined High Group	0.23	-0.48	-0.05	16.2	10.9
Combined Low Group	0.15	-0.39	-0.05	15.4	10.6

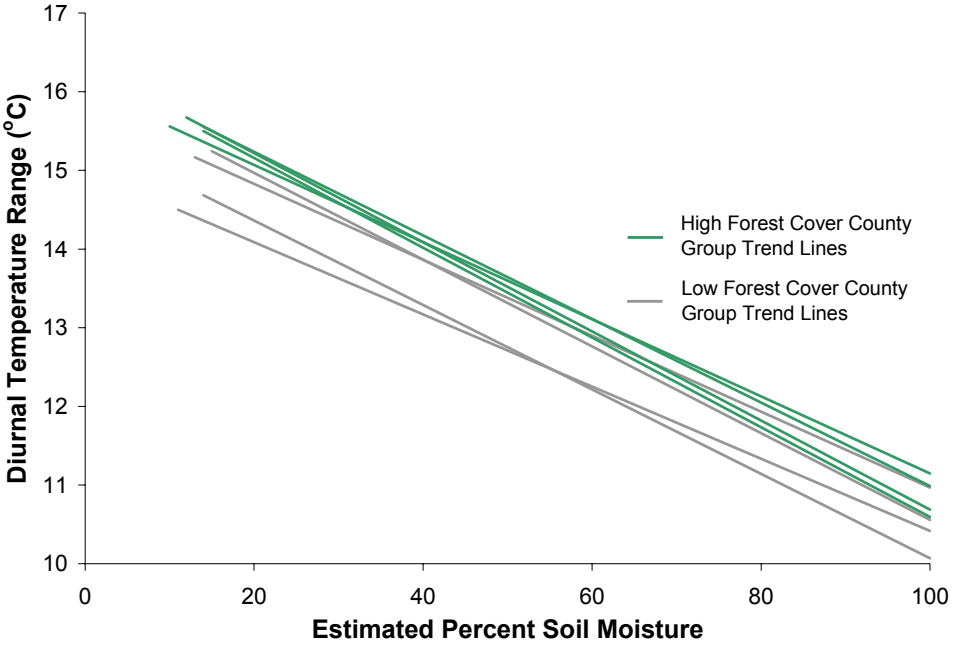


Figure 4.18. Graphical display of trend lines of DTR as described in Table 4.15.

As a final test to confirm the differences in these regression lines, individual days with minimal direct solar radiation were removed from the linear regression analysis. This was done by empirically estimating which DTRs correspond to cloudy days in a similar way as described by Geerts (2003):[6]

$$T_{DTR} = 26.5 - 3.1C \qquad (4.1)$$

[6] Geerts's method was intended to estimate the mean monthly diurnal temperature range, but the method is still appropriate at daily time-steps.

where T_{DTR} is the daily DTR and C is the cloudiness measured as the fraction of time with broken clouds (6 oktas) to cloudy conditions (8 oktas). Based on this equation (using okta values of 6 or greater), days with DTRs less than 7.9 ^{o}C were removed from the regression analysis. The new regression lines in Figure 4.19 still show higher DTRs for the HFCG, although the differences diminish as the soil moisture increases. Thus the observation holds that the HFCG has higher DTRs than the LFCG as the soil moisture decreases. This result is explored further in the next four tests.

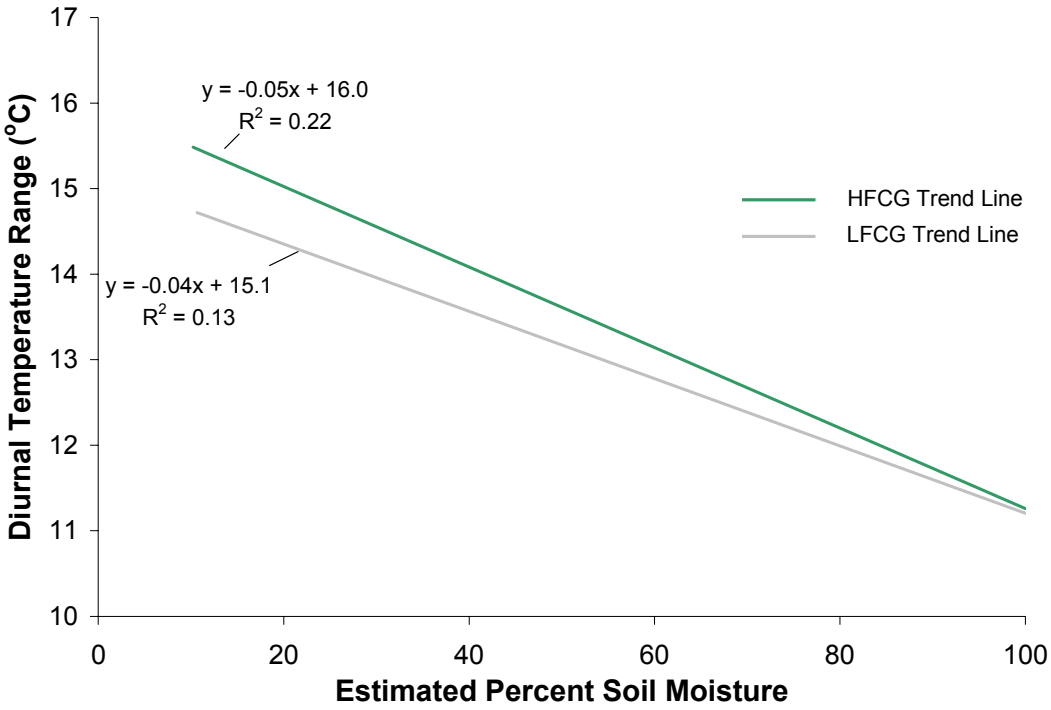


Figure 4.19. Same as Figure 4.17 except with cloudy days (≥ 6 Oktas) removed from the analysis.

4.7.2 DTR during Stress Periods

In Figure 4.20, ogives are plotted for the average DTR during a stress period. That is, regardless of the length of the stress period, is there a statistically significant difference between the two groups' mean DTR during a stress period? The results as mentioned above are somewhat counterintuitive. The HFCG has a higher temperature range than the LFCG. The LFCG has a greater range in average DTRs with a minimum mean diurnal temperature range of 7 ^{o}C compared to a mean minimum of 10 ^{o}C for the HFCG during stress periods. The overall mean differences are statistically significant (t-statistic = 5.26, p = 0.000).[7]

Figure 4.21 continues the pattern. In this figure, instead of the average DTR during stress periods, the ogive of every daily DTR during a stress period is shown. As in the previous test, the HFCG had higher probabilities of higher DTRs than the LFCG. The differences were statistically significant at the 0.01 level with a T-statistic of 13.77 (p = 0.000).

[7] Because the temperature data are normally distributed, the student's t-test was used for the hypothesis testing in this section.

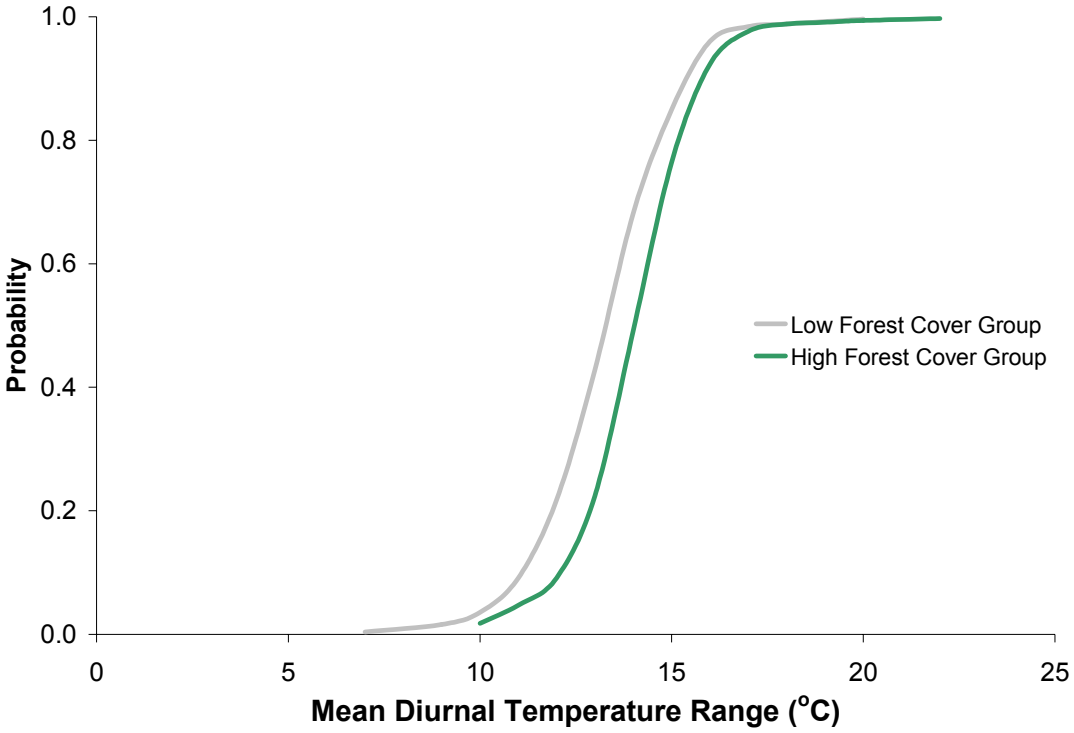


Figure 4.20. Mean DTR during stress periods (less than 35% soil moisture) for HFCG and LFCGs.

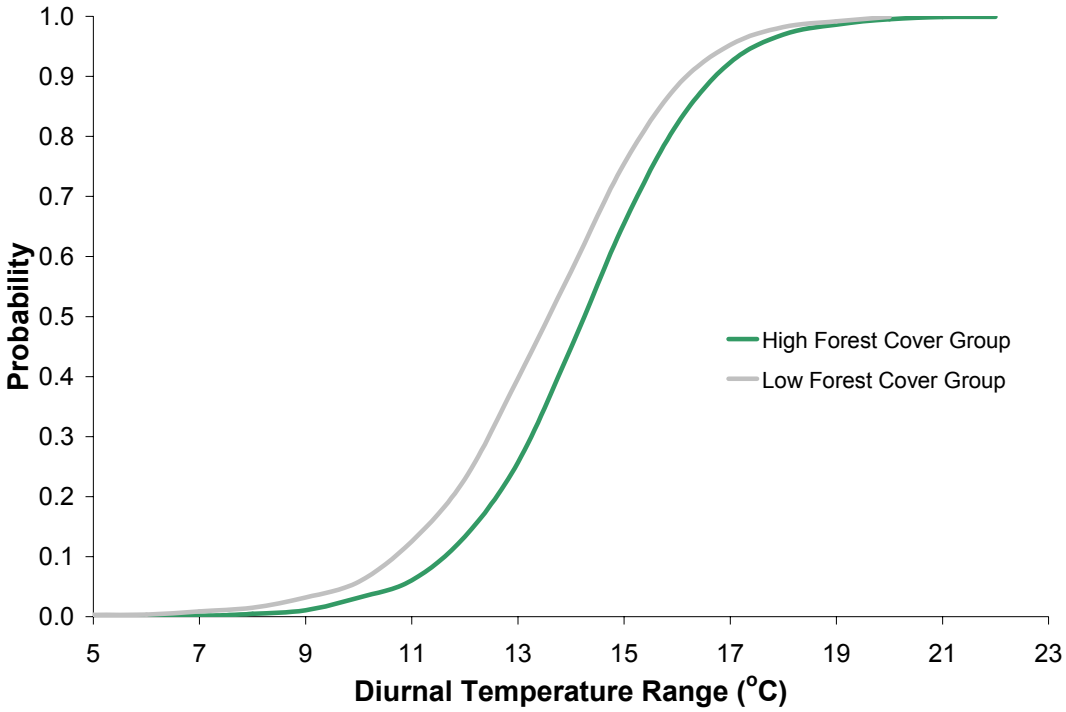


Figure 4.21. Same as Figure 4.20 except figure shows probability values for all DTRs during stress periods instead of the mean DTR during stress periods.

Figure 4.22 divides the previous test into increments or bins of ten-day stress periods. This is a similar concept to a histogram, but these figures are a second derivative of the DTR. To understand this concept examine Table 4.17 where the relative cumulative frequency is calculated for every temperature occurrence for days that are in at least the tenth day of a stress period, but no more than the twentieth day. We see in this table, for example, that there were 37 instances of a 14 degree DTR for days that have been in a stress period of at least 11 days but less than 20 days.

Table 4.17. Relative cumulative frequency of a DTR (in degrees Celsius) for a stress period length of 11 to 20 days for the LFCG.

24 Hour Temp Range	Count of days during 11-20 day stress period	Relative Cumulative Frequency
7	2	0.010
9	4	0.029
10	10	0.078
11	14	0.146
12	24	0.263
13	20	0.361
14	37	0.541
15	34	0.707
16	25	0.829
17	16	0.907
18	12	0.966
19	4	0.985
20	2	0.995

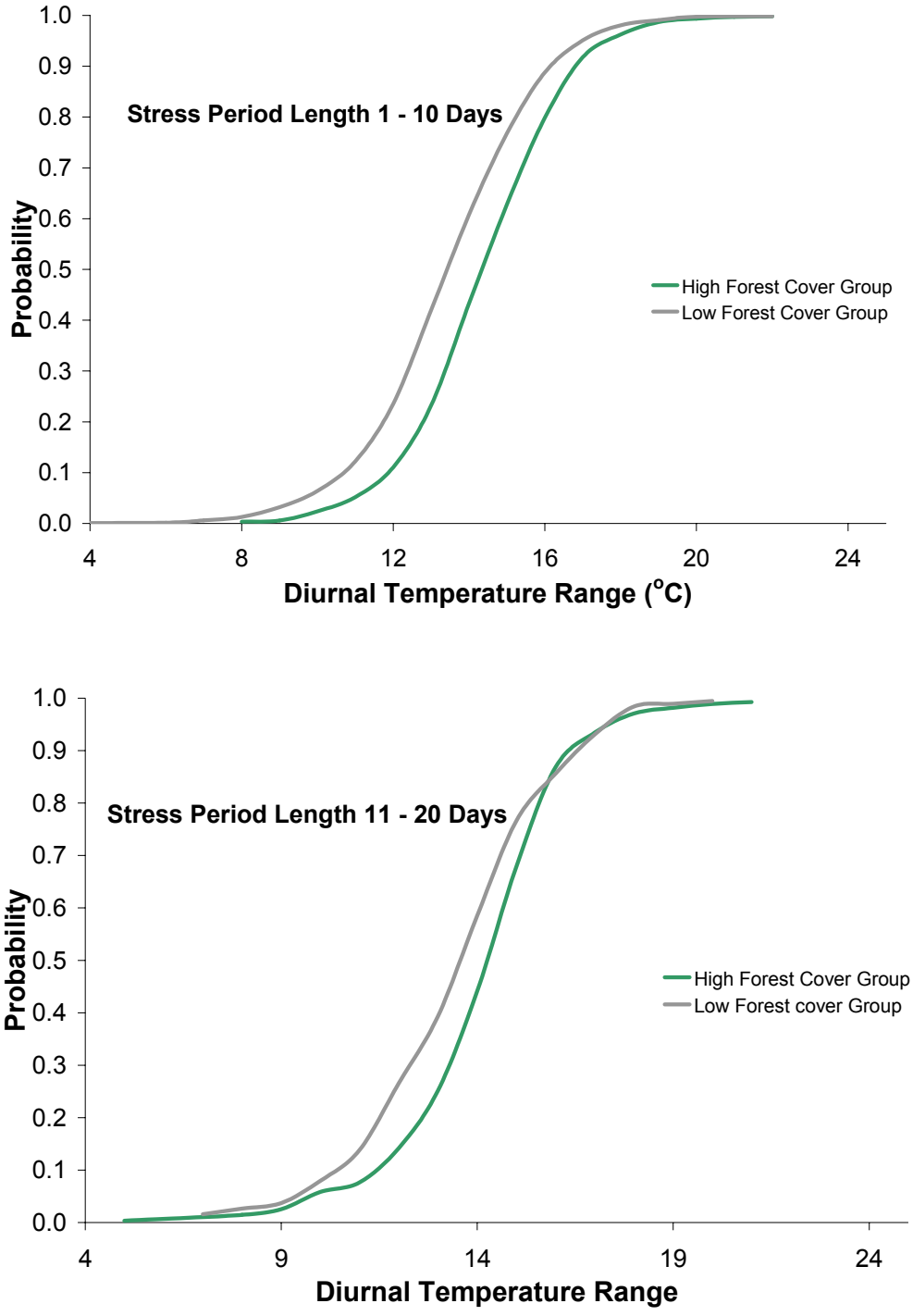


Figure 4.22. Distribution of diurnal temperature range probabilities over ten day stress periods.

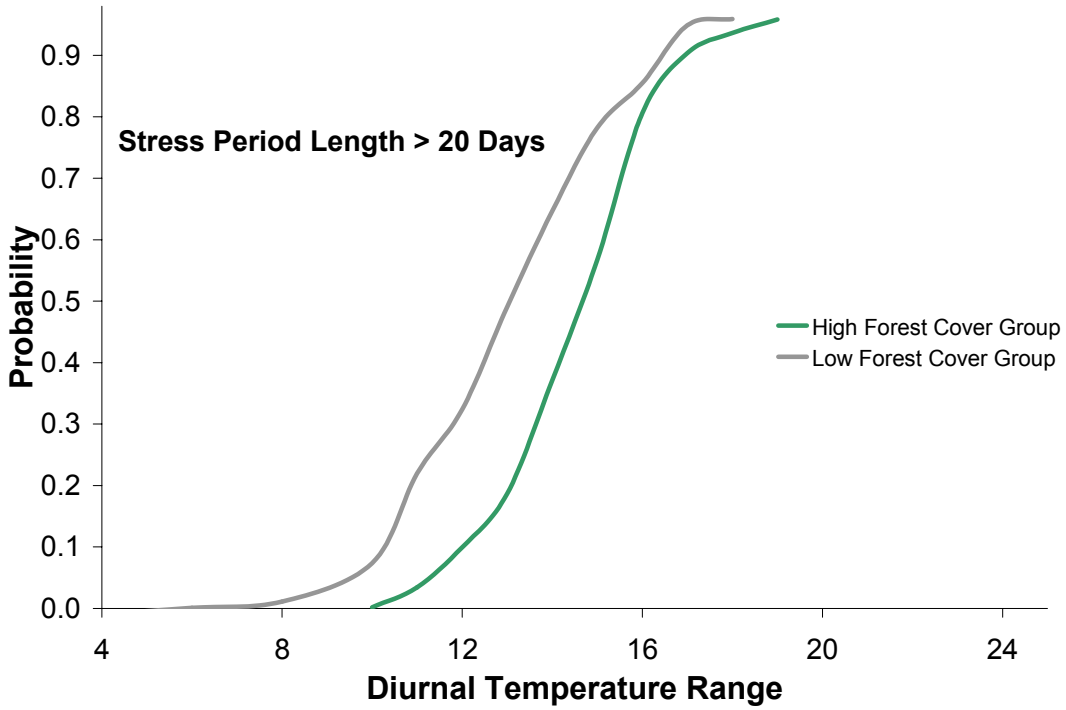


Figure 4.22. Continued.

The purpose of this test is two-fold. One, it examines the distribution of DTRs as the length of the stress period increases. This addresses whether longer periods of soil moisture stress are concurrent with larger temperature ranges (thus indicating hotter days and possibly cooler nights). It also addresses whether the slightly lower precipitation amounts in the LFCG are associated with larger DTRs over varying stress length periods. The results as summarized in Table 4.18 were similar to the previous two tests. For every stress period length, the LFCG experienced smaller DTRs than the HFCG.

Table 4.18. Results of student's t-test comparing average diurnal temperature range for three stress period lengths.

Statistic	Stress Period Length		
Mean	1 to 10 Days	11 to 20 Days	> 20 Days
High Forest Cover Group	14.8	14.5	14.8
Low Forest Cover Group	13.9	13.9	13.3
Standard Deviation	1 to 10	11 to 20	> 20
High Forest Cover Group	2.1	2.2	1.9
Low Forest Cover Group	2.2	2.4	2.5
T-Test	1 to 10	11 to 20	> 20
T-Value	10.7	2.8	4.7
p-Value	0.000	0.006	0.000

4.7.3 DTR below 50% SM

The last test examined the average temperatures for each group once a stress period began until the soil moisture reached 50% of field capacity (Figure 4.23). DTRs were still smaller for the LFCG. There was a slight shift in the results where the two groups had similar temperature ranges at the low end of the range (e.g. 6 – 10 ^{o}C). In general though, the LFCG still experienced smaller DTRs (mean HFCG = 12.75, mean LFCG = 12.20). The results were statistically significant at the 0.05 level with a p-value of 0.03.

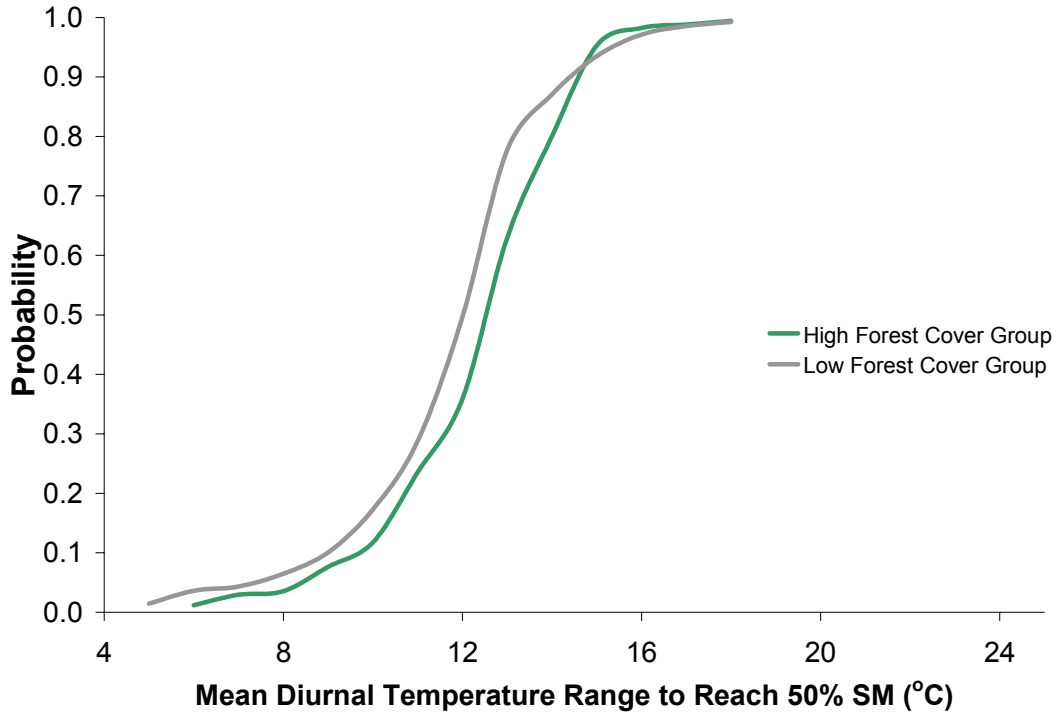


Figure 4.23. Mean diurnal temperature range during periods between the end of a stress period until the soil moisture has reached 50% of field capacity.

Every test analyzing temperature response to moisture stress conditions indicated smaller DTRs for the LFCG. This is consistent to what has been assumed or inferred from many model results in the past. (Charney 1975, Fedemma et al. 2005, etc.). Past studies have indicated that deforestation increases surface albedo causing a cooling effect on temperature (Bonan 2001). However some models suggest that deforestation reduces convective precipitation and cloud cover and increases sensible heat fluxes while reducing latent heat fluxes (Bounoua et al. 2002). This does not appear to be the case in this research since these past studies focused on total

deforestation in tropical and sub-tropical regions (versus partial deforestation in a sub-tropical to mid-latitude climate).

4.7.4 CV Analysis of Temperature

Although all these tests showed higher diurnal temperature ranges for the HFCG, the CV values for the two groups indicated that the HFCG had lower CV values (which is consistent with the higher standard deviations for the LFCG). To compare the two groups, the sea level temperatures were first calculated for each individual county group using the environmental adiabatic lapse rate:

$$T_{sl} = T_0\left(E\frac{6}{1000}\right) \qquad (4.2)$$

where T_{sl} is the daily sea level temperature to be determined (maximum or minimum), T_0 is the original daily temperature, and E is the mean elevation of the county group. The result of estimating the sea level temperature is the removal of the effects of elevation on temperature. This makes the direct comparison of the CV values between the two groups possible.

The results of the CV comparison for the maximum and minimum temperatures are presented in Figure 4.24. The CV values for the LFCG were skewed towards larger values compared to the HFCG (Table 4.19). This was the case for both the maximum and minimum daily temperatures. A t-test for difference of means showed that the two groups were significantly different for both the maximum daily temperature ($p < 0.001$), and the minimum daily temperature ($p < 0.001$). To ensure that the geographic make-up of the county groups was not biasing the results (i.e.

temperature ($p < 0.001$), and the minimum daily temperature ($p < 0.001$). To ensure that the geographic make-up of the county groups was not biasing the results (i.e. because of undue ocean influence in the HFCG), the Choctaw, AL high forest cover county group (close to the Gulf of Mexico) and the Morgan, AL low forest cover county group (near the Tennessee border), were removed from the CV analysis. The new comparison indicated that the two groups' CV values were still significantly different from each other ($p < 0.001$) with higher variability in the LFCG.

Table 4.19. Summary statistics comparing coefficient of variability for air temperature in the HFCG and LFCG.

CV Summary	**Maximum Temperature**	**Minimum Temperature**
Statistic		
Mean		
High Forest Cover Group	5.8	7.1
Low Forest Cover Group	6.6	8.0
Standard Deviation		
High Forest Cover Group	2.3	3.6
Low Forest Cover Group	2.4	4.0

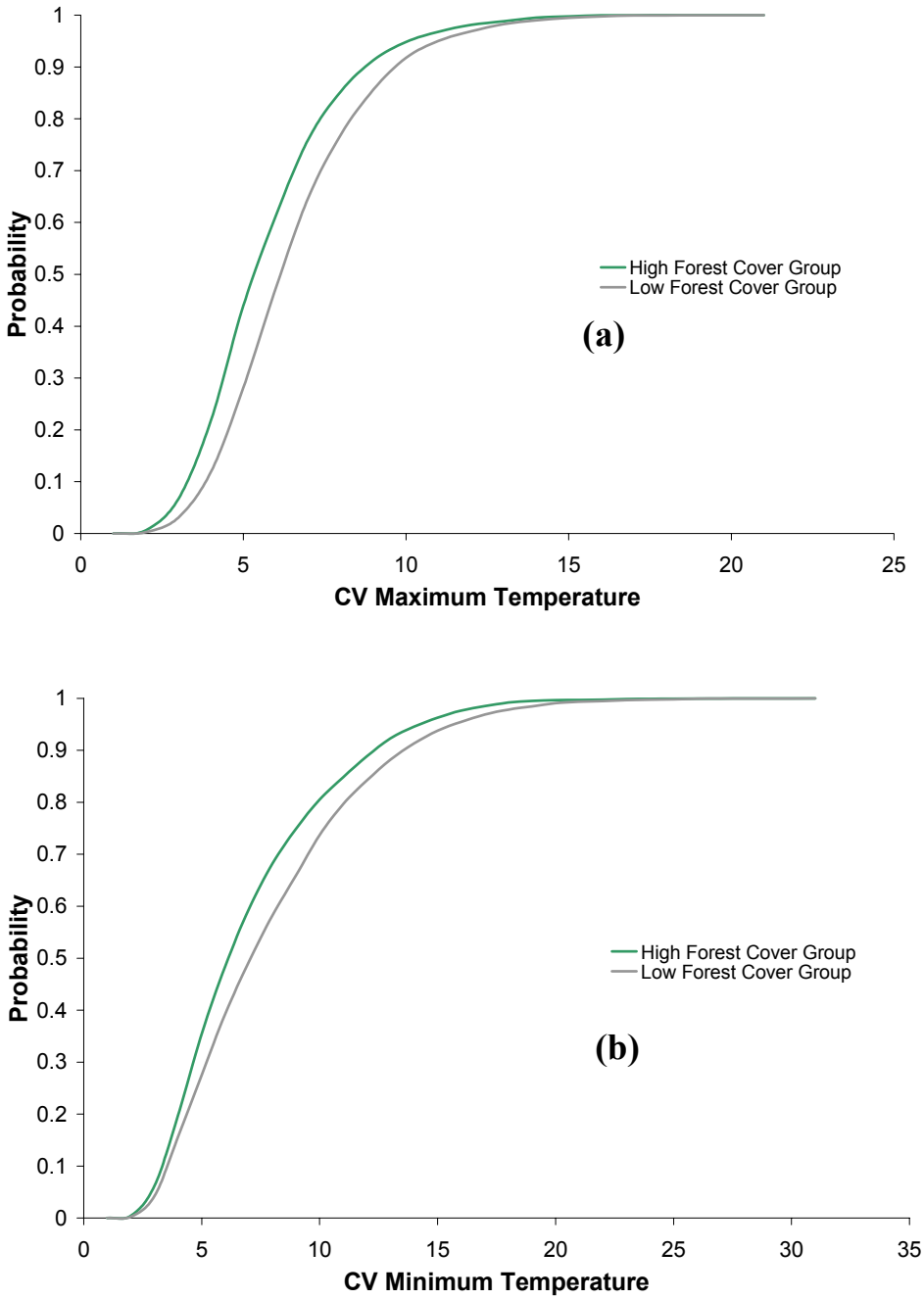


Figure 4.24. Ogive comparison of CV values for maximum **(a)** and minimum **(b)** daily air temperatures for the HFCG and LFCG.

4.7.5 Temperature Analysis - Discussion

This study's temperature analysis showed higher DTRs and lower variability for the HFCG and vice versa for the LFCG. There have been examples in past studies where open-canopy forests have higher temperatures (and therefore larger diurnal temperature ranges) than neighboring open areas (Kittredge 1948). Large plantations of Loblolly and Longleaf pine could contribute to higher temperatures by simultaneously absorbing more solar energy (through a lower albedo) and heating the air due to the open canopy.

This explanation can be reasoned by returning to Figure 4.19. Perhaps the effect of higher evapotranspiration rates in the HFCG is not enough to limit the diurnal range when soil moisture is low. Hence, the lower albedo in the HFCG will allow more energy to be absorbed and for daytime temperatures to rise. As the soil moisture increases, evapotranspiration increases at a faster rate in the HFCG than in the LFCG and moderates the effect of lower albedo. Thus the diurnal temperature ranges for the two groups converge as the soil moisture reaches saturation.

This still does not explain the greater variability in the LFCG. It's possible that the greater heterogeneity in the land surface (some of the low forest cover county groups still have 50% forest cover) in the LFCG causes higher variability in temperatures. Forested areas would experience higher DTRs and vice versa for the non-forested areas. Thus, the overall variability is high, but the DTR is lower than the areas that are completely forested. These interesting results, and the additional questions they generate underscore the need for further study into how the land surface affects the climate system.

Chapter 5

SUMMARY AND CONCLUSIONS

The goal of this thesis was to determine the impact of forest cover on the climate of the Southeast. The methods described in Chapter 3 would then establish how large an impact terrestrial vegetation has on the climate system for meso-scale time periods and regions. The research hypotheses were tested using a data exploration method that employed several techniques to isolate the changes in climate related to forest cover levels and changes over time. This chapter presents a summary of this research, the study's contributions to knowledge in the field, and how this research can be used in the future.

5.1 Summary of Results

The results from sections 4.6 and 4.7 suggest that forest cover does not affect precipitation but does have an impact on temperature. Five objectives were outlined in Chapter 1 detailing how this study would proceed and with each the main results of the analysis are presented which include:

Objective 1: To develop a method to determine spatially and temporally contiguous county groups of forest cover from US Department of Agriculture (USDA) forest surveys.

Result: An algorithm was successfully developed to create viable comparisons between forest cover groups based on clustering of forest cover survey data and interpolation of cooperative station data. The DEM-aided interpolation method

satisfactorily interpolated temperature and precipitation data from cooperative weather stations to a grid of the study area. In addition, the clustering procedure was able to create groups that had small amounts of missing climate data as well as similar forest cover levels through time.

Objective 2: To determine the impact of forest cover on air mass character and frequency.

Result: A multiple linear regression analysis of the effect of elevation, distance from the ocean, and forest cover on air mass character indicated that forest cover had little impact on the dominant summer air mass's character. While statistically significant, little of the model variance was explained by forest cover level. In addition, no discernable trends were seen in air mass frequency that could be linked to forest cover trends over time.

Objective 3: To determine how forest cover alters the precipitation regime of these county groups.

Result: No significant differences in precipitation were found between groups with high levels of forest cover and low levels of forest cover. The probability of precipitation between the two groups was not significantly different.

Objective 4: To determine how forest cover influences the difference between and the magnitude of maximum and minimum daily temperatures.

Result: The low forest cover group (LFCG) had smaller diurnal temperature ranges (DTR) of ~0.3 ^{o}C than the high forest cover group (HFCG). However, the low forest cover group also had a high coefficient of variability (CV) for both maximum and minimum temperatures compared to the HFCG.

Objective 5: To determine how forest cover alters the moisture and temperature regime during times of vegetation stress.

Result: A negative linear relationship was found between DTR and soil moisture (SM) of roughly 0.5 ^{o}C per 10% increase in soil moisture. Differences in this relationship between the two groups increased as the soil moisture decreased. The HFCG had increasing DTR as the soil moisture increased. When clouds were removed from the analysis, the two groups had similar DTRs at soil moisture saturation. No differences were found between the distribution of the size or the amount of precipitation during times of vegetation stress (< 35% SM). Stress period length did not significantly differ between the two groups. In addition, the length of

the stress period did not affect the differences between the two groups' DTR; the low forest cover group consistently had lower DTRs.

This study has shown that the amount of forest cover in the Southeast did not have a significant effect on the probability of precipitation or the amount of precipitation. However, the amount of forest cover did affect temperature. The higher DTRs found in the HFCG could reflect the lower albedo and location change of the radiational cooling level (surface versus canopy). Areas with low forest cover have a higher albedo that reflects more solar energy. In addition, as reforestation occurs, radiational cooling moves from the ground to the canopy. Also, as the planetary boundary layer is extended upward, more heat and energy are retained near the surface, possibly leading to increased temperatures (and DTRs) in the HFCG. The higher variability in DTR in the LFCG is most likely a function of the greater heterogeneity of the land surface in this group. Areas in the LFCG that have high percentages of forest cover would have higher DTRs than nearby areas in the LFCG without forest cover. Thus the overall effect of having large patches of both forested and non-forested regions in the LFCG is higher variability in the DTR.

The results of this study are generally consistent with the results of previous research has shown to be the effect of the land surface and reforestation on climate. Bonan's (2001) study also found higher DTRs in regions with high forest cover compared to agricultural areas (i.e. the Northeast U.S. compared to the Midwest U.S.). However, this study had differing results from the temperature response to land cover change found in Englehart and Douglas's (2005) study of Mexican DTR. The precipitation results also differed from what has been theorized by Anthes (1984) or modeled by Bounoua et al. (2002) and Pielke (1999). Three possibilities could explain this difference. One is that these studies were set in tropical or near-tropical

locations where evaporative cooling is more important that albedo changes caused by reforestation. Another difference that could explain the discrepancy in the precipitation findings is that the differences in forest cover levels in this study were not large enough to affect the hydrologic cycle. The modeling studies mentioned above were focused on total deforestation. Such a scenario would be expected to have a larger impact on the amount of moisture that would be available for storage and evaporation. The final possibility is that many of the modeling studies that predict precipitation decreases as a result of deforestation are overestimating the effect of forest cover on the hydrologic cycle. These differences and uncertainties highlight the need for further improvement and expansion of this study.

5.2 Research Improvements

Several areas of this thesis could be expanded to further analyze and understand the effect of reforestation on climate. This is a meso-scale study both in time and space, and the problems with accuracy and resolution have been dealt with as best as possible, but nonetheless issues still remain. For example, the resolution of the forest cover data used in this research is on the county level (acres of forest for each county) and thus does not show the extent of forest cover within the county. Are the forested and non-forested areas evenly dispersed throughout the county or are they segregated?

Satellite data can answer this question but imagery is only available back to the early 1970s. Aerial photographs are another alternative. The Department of Agriculture (USDA) has maintained an ongoing aerial photography program since the mid-1930s. These data would be ideal to determine the heterogeneity of the forest

cover through time. However, the time and expense required to undertake such an endeavor was not feasible for this study.

This research was also constrained by the availability of climatic data. The vast majority of the climate data only went back to the middle of the 20th century when this study began, but major reforestation of the Piedmont began following the boll weevil infestation in the 1910s and accelerated during the Great Depression. During the 1930s, the combination of the collapse of the farm economy and a large land buy-out program by the federal government meant that some of the most dramatic reforestation had already taken place by the time extensive climate and forest records were available.

A potential solution is to utilize weather data from old railroad stations. Most of these data begin in the late 19th century and would capture the meteorological conditions of the Piedmont at the height of the cotton-based economy. These data, combined with data from Agricultural Experiment Stations and various other governmental and academic weather offices may be large enough in extent that they would produce an historical climate dataset with a satisfactory level of station density. In addition, as more and more of the climate record is digitized from the cooperative station network, it becomes feasible to extend the period of study of this research back to times of extensive deforestation. These data could be combined with historical proxies of forest cover data such as agricultural census data, to estimate the effects of almost total deforestation on the climate. Such a study would be valuable for testing how well current models predict the effect of deforestation on the climate.

Alternatively the study could be scaled-down spatially and temporally to focus on three types of land covers: a heavily forested area, a non-forested area, and

an area in transition from non-forested to forest. These areas would need to be spatially close to each other and climatologically similar. The methodology would shift to intensive analysis of a small number of stations (or one station) rather than a broad-based data exploration study such as this thesis. The goal would be to confirm the impact of forest cover on climate through measurement and estimation of the respective soil moisture and energy fluxes (sensible and latent) in all areas through time. Similar studies have been done over the years (e.g. Pinty et al. 1989) but not over a period of more than a few seasons.

Another alternative is to rely more heavily on remotely sensed data to better delineate large spatially contiguous areas of forest cover versus non-forested areas. This study has determined which cooperative stations have a sufficient amount of climatological data (although as more data becomes available this list should expand). This knowledge could be used as a starting point to examine the areas surrounding these stations using satellite imagery. Promising areas would have the same land cover types as stated above. With the suitable areas selected, the previously mentioned historical aerial photographs from the USDA would determine which areas to include for final analysis. The study could then be expanded to include the effect of different types of forest cover (e.g. oak-hickory forest versus loblolly pine) and agriculture (e.g. pasture versus cotton). This approach is tedious and expensive, but it may help to better elucidate the effects of reforestation and forest cover on climate.

Appendix A

COUNTY MAKE-UP OF CONTIGUOUS COUNTY GROUPS

The table below lists the individual counties that comprise contiguous county groups that were created with the forest and climate clustering procedure (see Figure 4.1 for a map of the county groups). The county groups are segregated by the three forest cover groups: high, medium, and low forest cover.

High Forest Cover Group		Medium Forest Cover Group		Low Forest Cover Group	
County Group	**Counties**	**County Group**	**Counties**	**County Group**	**Counties**
Choctaw, AL	Choctaw, AL	Russell, AL	Bullock, AL	Morgan, AL	Madison, AL
	Clarke, AL		Macon, AL		Marshall, AL
	Monroe, AL		Pike, AL		Morgan, AL
Appling, GA	Appling, GA		Russell, AL	Barrow, GA	Barrow, GA
	Atkinson, GA	Talladeg, AL	Calhoun, AL		Clarke, GA
	Berrien, GA		Cherokee, AL		Oconee, GA
	Coffee, GA		Etowah, AL		Walton, GA
	Jeff Davis, GA		Talladeg, AL	Lee, GA	Crisp, GA
	Lanier, GA	Bartow, GA	Bartow, GA		Dougherty, GA
	Tattnall, GA		Floyd, GA		Lee, GA
Dawson, GA	Dawson, GA	Chesterfield, SC	Chesterfield, SC		Mitchell, GA
	Lumpkin, GA		Kershaw, SC	Iredell, NC	Cabarrus, NC
	Pickens, GA		Lancaster, SC		Iredell, NC
	White, GA	Darlington, SC	Darlington, SC		Rowan, NC
Jones, GA	Greene, GA		Dillon, SC	Orangeburg, SC	Bamburg, SC
	Jasper, GA		Marlboro, SC		Calhoun, SC
	Jones, GA		Sumter, SC		Orangeburg, SC
	Monroe, GA	Greenwood	Greenwood, SC		Sumter, SC
	Putman, GA		Laurens, SC		
	Twiggs, GA		Newberry, SC		
	Upson, GA	Marengo, AL	Greene, AL		
	Wilkes, GA		Hale, AL		
	Wilkinson, GA		Marengo, AL		
Fairfield, SC	Fairfield, SC		Perry, AL		
	Union, SC		Sumter, AL		
		Lamar, AL	Fayette, AL		
			Lamar, AL		
			Marion, AL		
			Pickens, AL		
		Butler, AL	Butler, AL		
			Conecuh, AL		
			Covington, AL		
			Monroe, AL		

Appendix B

AIR TEMPERATURE TRENDS FOR PIEDMONT COUNTY GROUPS

The following tables and figures show the maximum and minimum daily air temperature trends for each county group that resulted from the interpolation procedure outline in Chapter 3. The tables list the results of linear regression models that examined the correlations of the mean annual maximum and minimum temperature with time and forest cover. The figures display the daily temperature data over time. The discussion of these data is presented in Section 4.3. The results indicated that these data by themselves were not helpful in determining the impact of forest cover on the climate of the Piedmont.

Table B.1. Summary of linear regression tests evaluating summer maximum temperature trends over time by county group.

Maximum Temperature vs. Time		Slope	
High Forest Cover Group	Pearson's r	(^{o}C/year)	p-value
Choctaw, AL	-0.29	-0.02	0.04
Appling, GA	0.20	0.01	0.15
Fairfield, SC	-0.14	-0.01	0.32
Jones, GA	-0.07	-0.01	0.62
Dawson, GA	0.06	0.01	0.73
Low Forest Cover Group			
Iredell, NC	-0.24	-0.01	0.08
Morgan, AL	-0.21	-0.02	0.18
Barrow, GA	0.15	0.01	0.29
Orangeburg, SC	-0.06	-0.01	0.67
Lee, GA	-0.05	0.00	0.71
Medium Forest Cover Group			
Bartow, GA	-0.44	-0.04	0.01
Butler, AL	-0.19	-0.01	0.18
Russell, AL	-0.22	-0.02	0.18
Chesterfield, SC	-0.21	-0.02	0.23
Greenwood, SC	-0.14	-0.01	0.34
Marengo, AL	-0.13	-0.01	0.35
Talladega, AL	-0.06	0.00	0.65
Lamar, AL	-0.04	0.00	0.78
Darlington, SC	-0.03	0.00	0.83

Table B.2. Same as Table B.1 except for minimum temperature over time.

Minimum Temperature vs. Time		Slope	
High Forest Cover Group	Pearson's r	(^{o}C/year)	p-value
Jones, GA	0.33	0.01	0.01
Fairfield, SC	0.27	0.01	0.05
Dawson, GA	0.28	0.01	0.11
Choctaw, AL	0.22	0.01	0.11
Appling, GA	0.07	0.00	0.65
Low Forest Cover Group			
Orangeburg, SC	0.36	0.02	0.01
Morgan, AL	0.35	0.02	0.03
Barrow, GA	0.27	0.01	0.07
Lee, GA	-0.23	-0.01	0.09
Iredell, NC	0.17	0.01	0.22
Medium Forest Cover Group			
Lamar, AL	0.49	0.03	0.00
Talladega, AL	0.41	0.02	0.00
Darlington, SC	0.34	0.01	0.01
Greenwood, SC	-0.30	-0.01	0.03
Russell, AL	0.17	0.01	0.32
Bartow, GA	0.14	0.01	0.41
Butler, AL	-0.10	0.00	0.47
Chesterfield, SC	-0.12	-0.01	0.50
Marengo, AL	-0.02	0.00	0.87

Table B.3. Linear regression results of maximum temperature versus percent forest cover.

Maximum Temperature vs. Forest Cover		Slope	
High Forest Cover Group	Pearson's r	(°C/year)	p-value
Choctaw, AL	-0.31	-0.15	0.02
Fairfield, SC	-0.27	-0.08	0.05
Appling, GA	-0.20	-0.03	0.16
Jones, GA	-0.15	-0.09	0.28
Dawson, GA	-0.03	-0.01	0.86
Low Forest Cover Group			
Iredell, NC	-0.18	-0.06	0.20
Morgan, AL	-0.19	-0.10	0.25
Lee, GA	-0.13	-0.08	0.34
Barrow, GA	0.03	0.01	0.86
Orangeburg, SC	0.01	0.00	0.96
Medium Forest Cover Group			
Darlington, SC	0.41	0.11	0.00
Bartow, GA	-0.31	-0.31	0.06
Greenwood, SC	-0.25	-0.08	0.07
Chesterfield, SC	-0.24	-0.06	0.16
Russell, AL	-0.23	-0.03	0.18
Butler, AL	-0.16	-0.05	0.27
Marengo, AL	-0.14	-0.04	0.31
Talladega, AL	0.08	0.03	0.57
Lamar, AL	-0.06	-0.02	0.71

Table B.4. Same as Table B.3 except for minimum temperature versus forest cover.

Minimum Temperature vs. Forest Cover		Slope	
High Forest Cover Group	Pearson's r	(°C/year)	p-value
Jones, GA	-0.32	-0.12	0.02
Appling, GA	0.22	0.02	0.12
Dawson, GA	-0.25	-0.05	0.16
Choctaw, AL	0.11	0.04	0.43
Fairfield, SC	-0.03	-0.01	0.82
Low Forest Cover Group			
Orangeburg, SC	0.39	0.06	0.01
Lee, GA	0.35	0.13	0.01
Iredell, NC	-0.30	-0.08	0.03
Morgan, AL	0.22	0.09	0.17
Barrow, GA	-0.15	-0.02	0.30
Medium Forest Cover Group			
Lamar, AL	0.45	0.11	0.00
Greenwood, SC	-0.39	-0.07	0.00
Bartow, GA	-0.23	-0.13	0.17
Russell, AL	0.20	0.02	0.25
Chesterfield, SC	-0.19	-0.03	0.27
Marengo, AL	0.12	0.03	0.39
Talladega, AL	-0.07	-0.02	0.64
Butler, AL	-0.04	-0.01	0.78
Darlington, SC	0.01	0.00	0.95

Table B.5. Number of county groups with slopes significantly different than zero stratified by max and min temperature and forest cover group.

Number of Significant County Groups (p <= 0.1)	Forest Cover	Time
Max Temperature	5	3
Min Temperature	6	10

Number of Significant County Groups (p <= 0.1)	Forest Cover	Time
High Forest Cover Group	3	4
Medium Forest Cover Group	5	5
Low Forest Cover Group	3	5

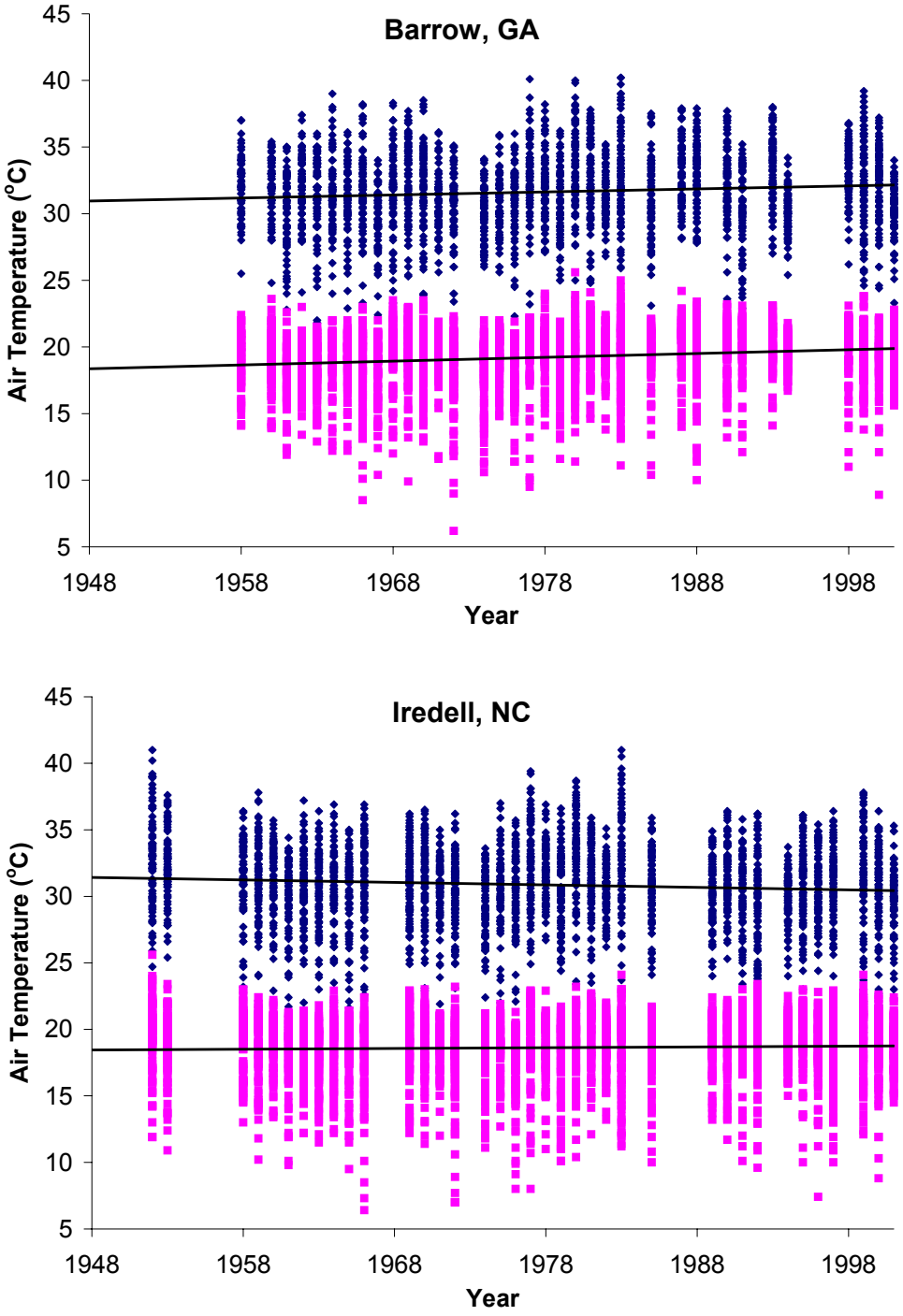
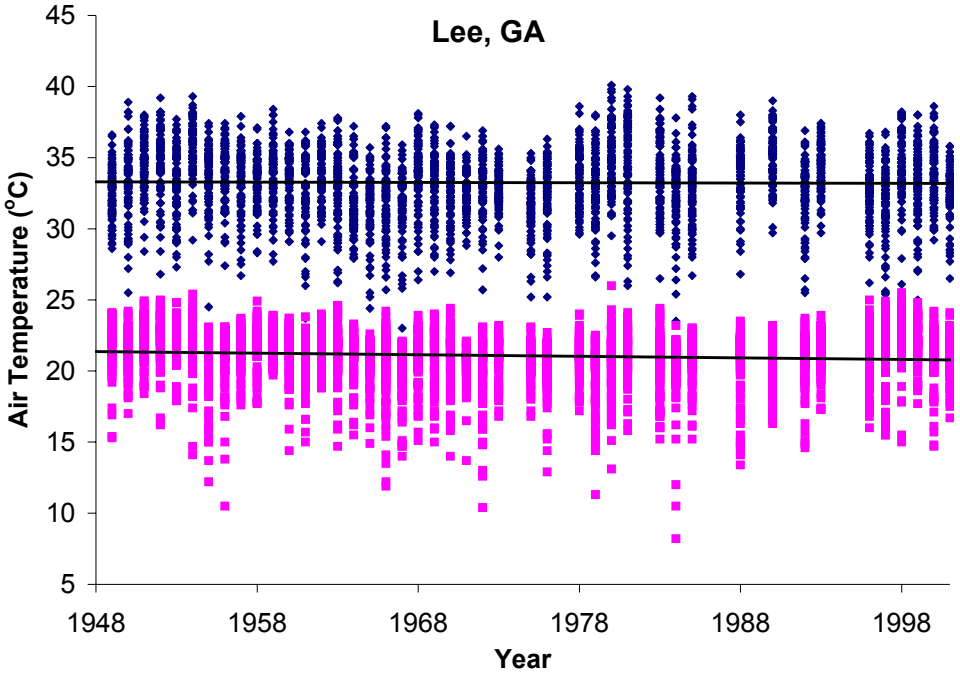


Figure B.1. Maximum (top-blue) and minimum (bottom-pink) daily summer temperature in degrees Celsius for low forest cover county groups.



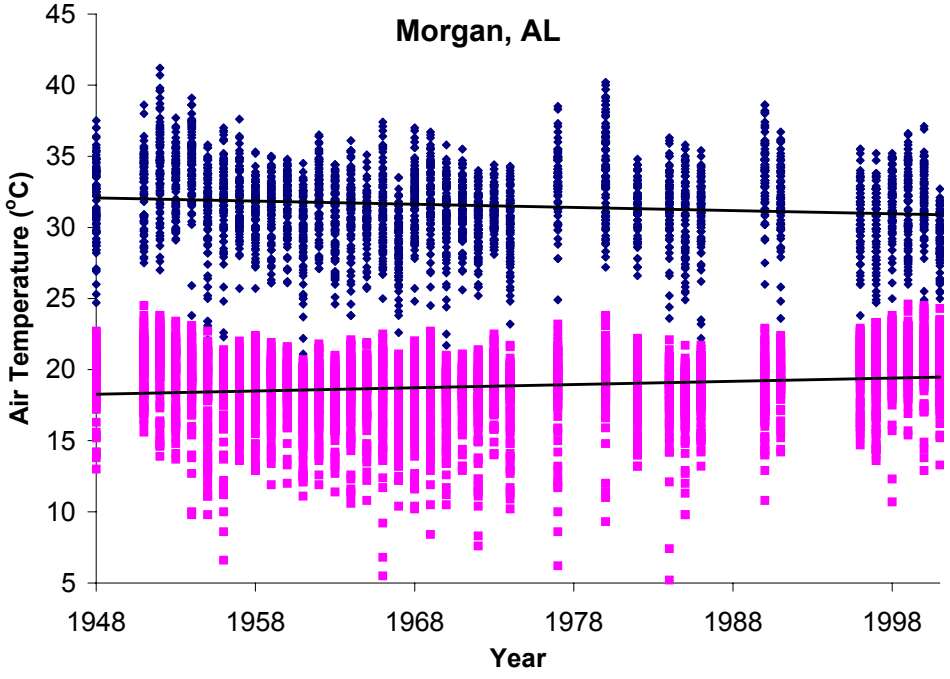


Figure B.1. Continued.

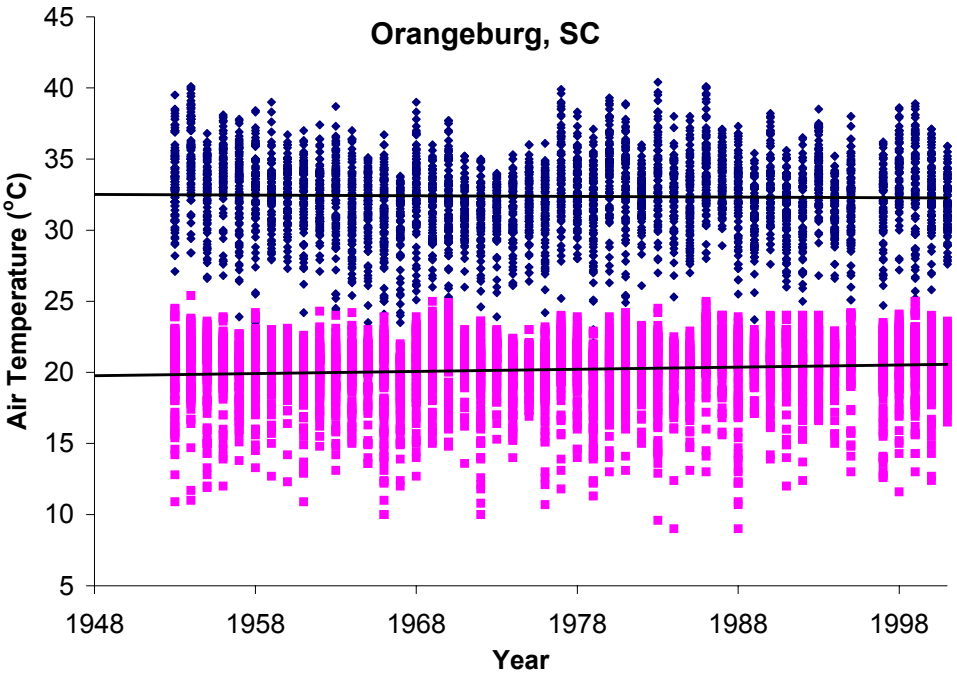


Figure B.1. Continued.

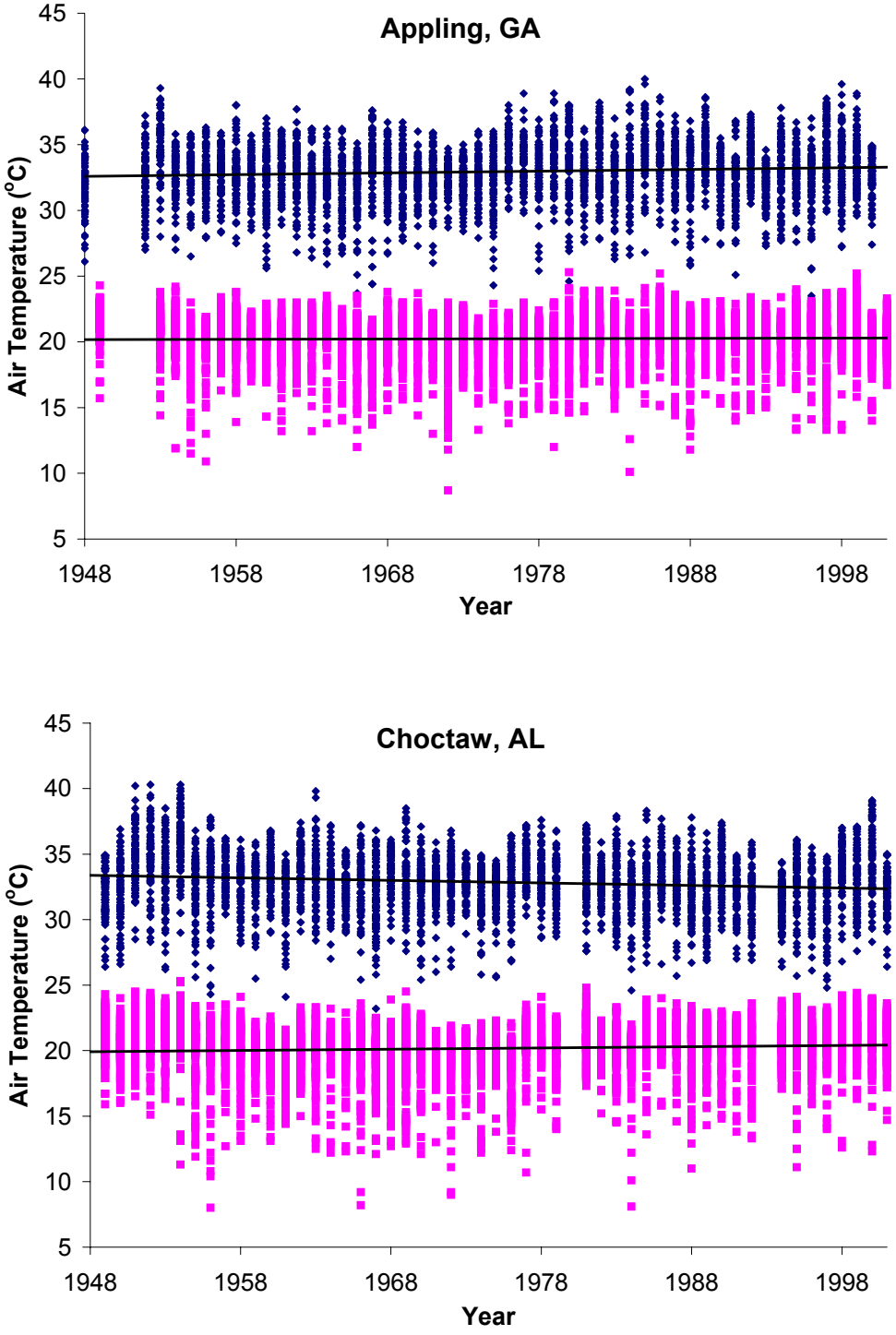
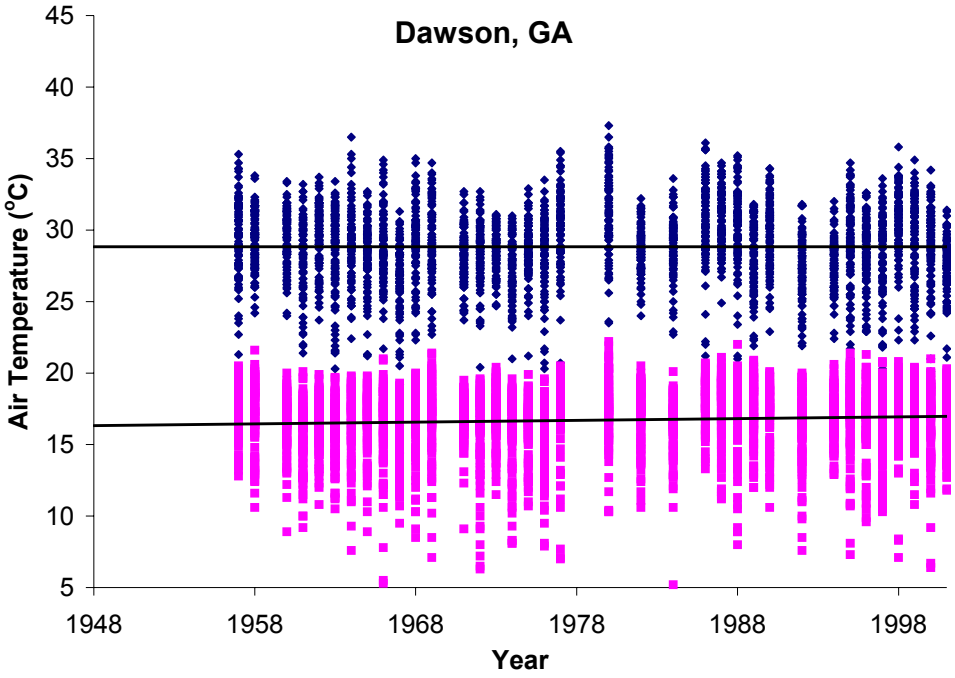


Figure B.2. Same as Figure B.1, except for the high forest cover cluster.



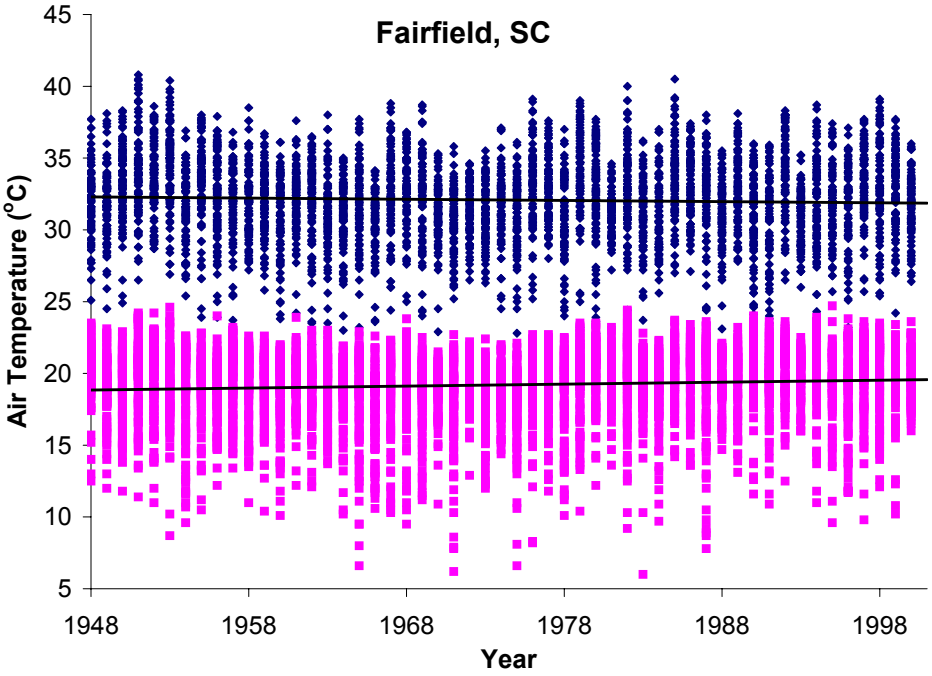


Figure B.2. Continued

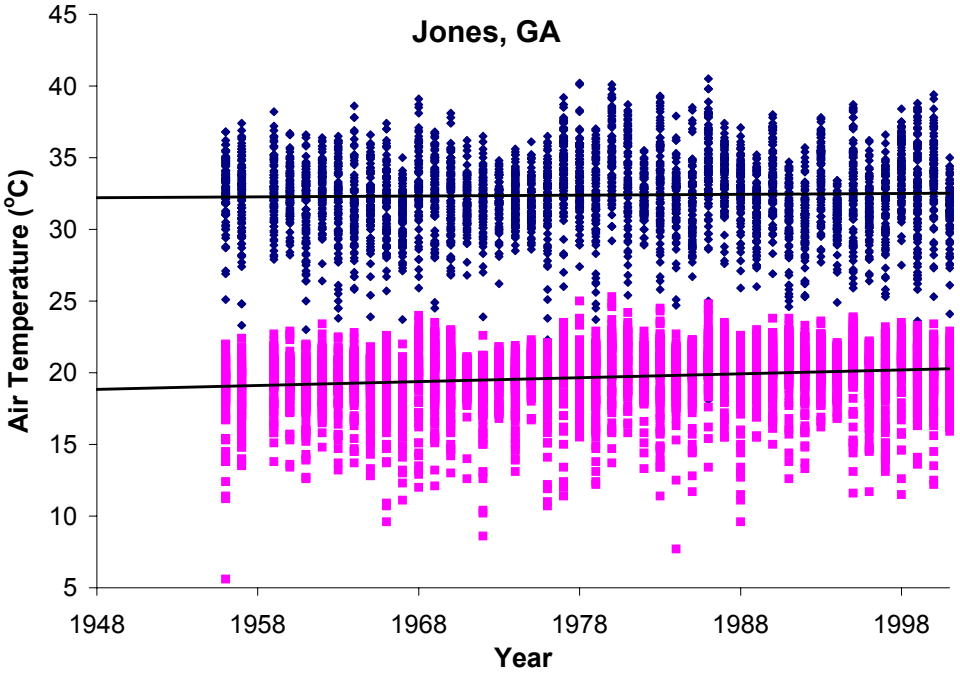


Figure B.2. Continued

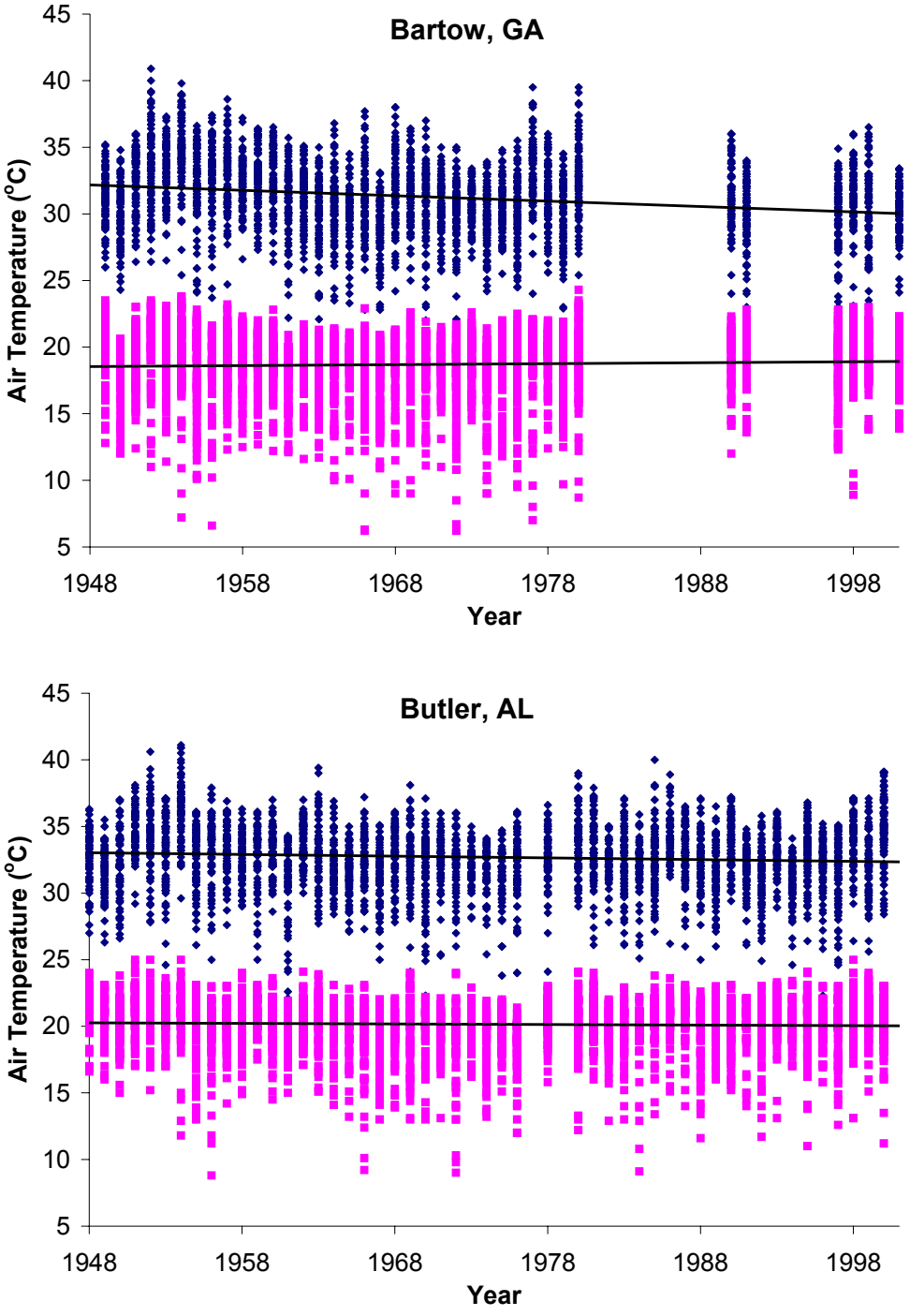
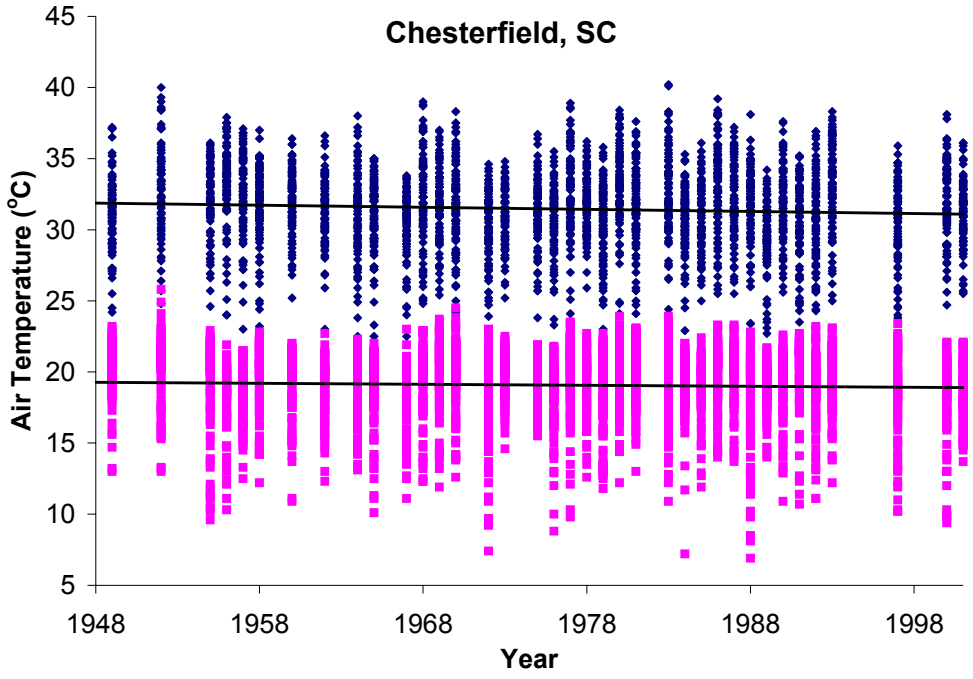


Figure B.3. Same as Figure B.1, except for the medium forest cover group.



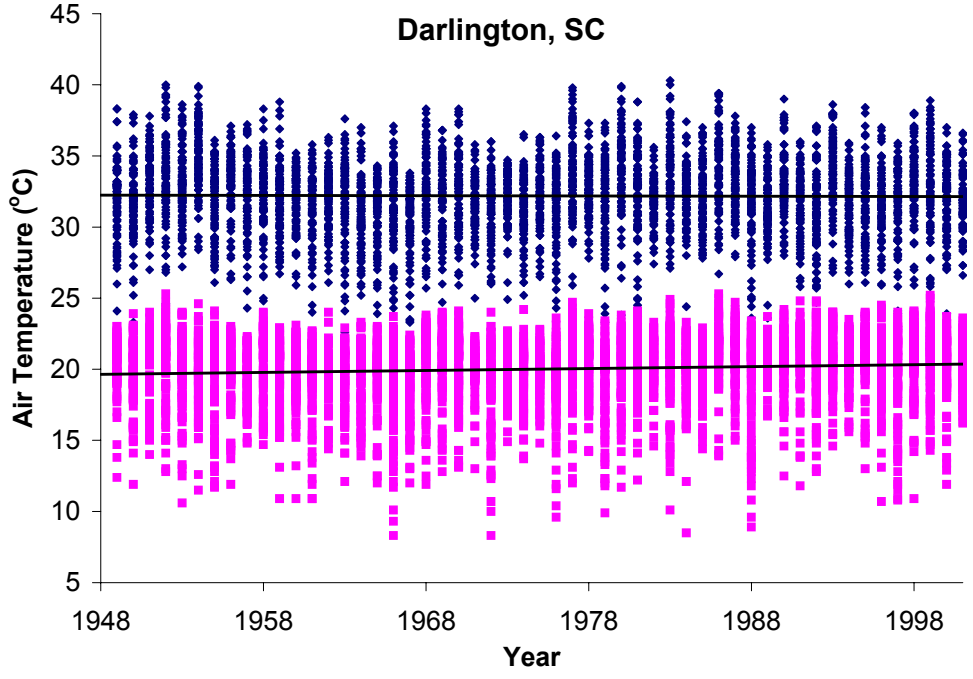
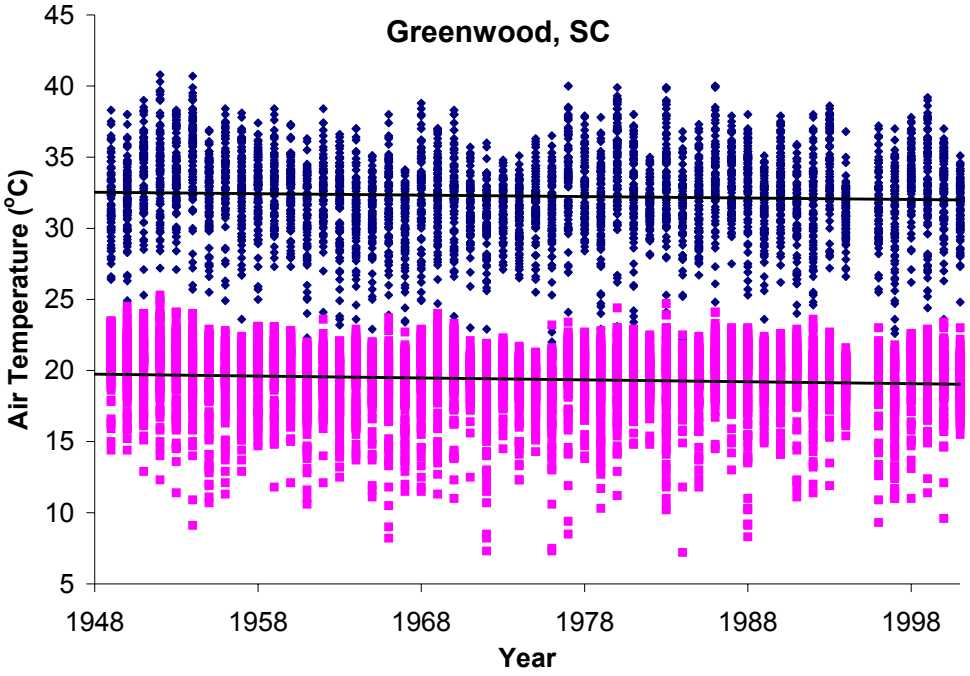


Figure B.3. Continued



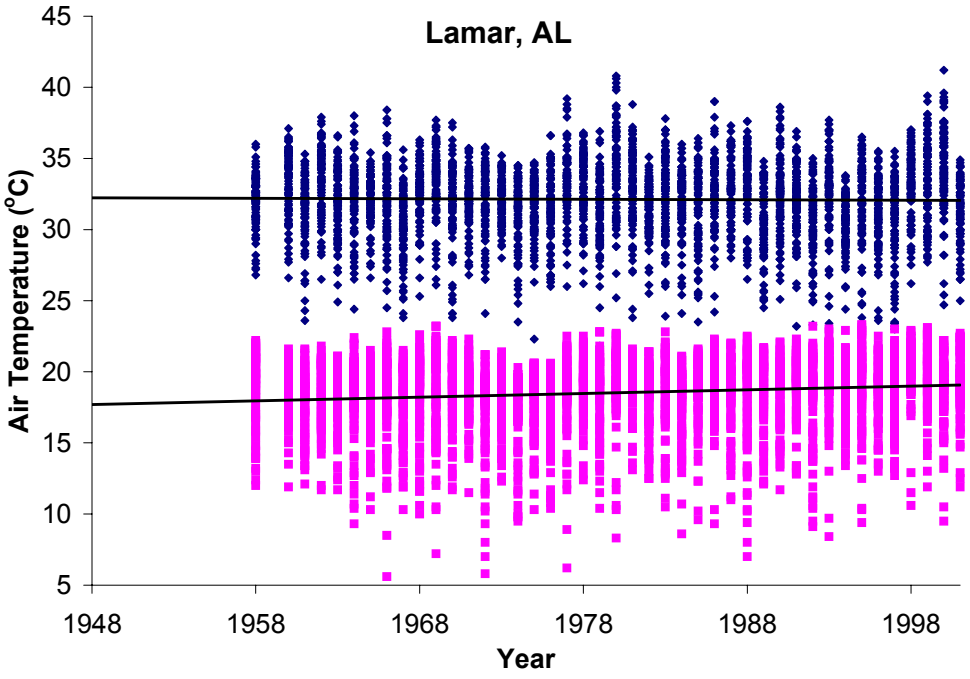
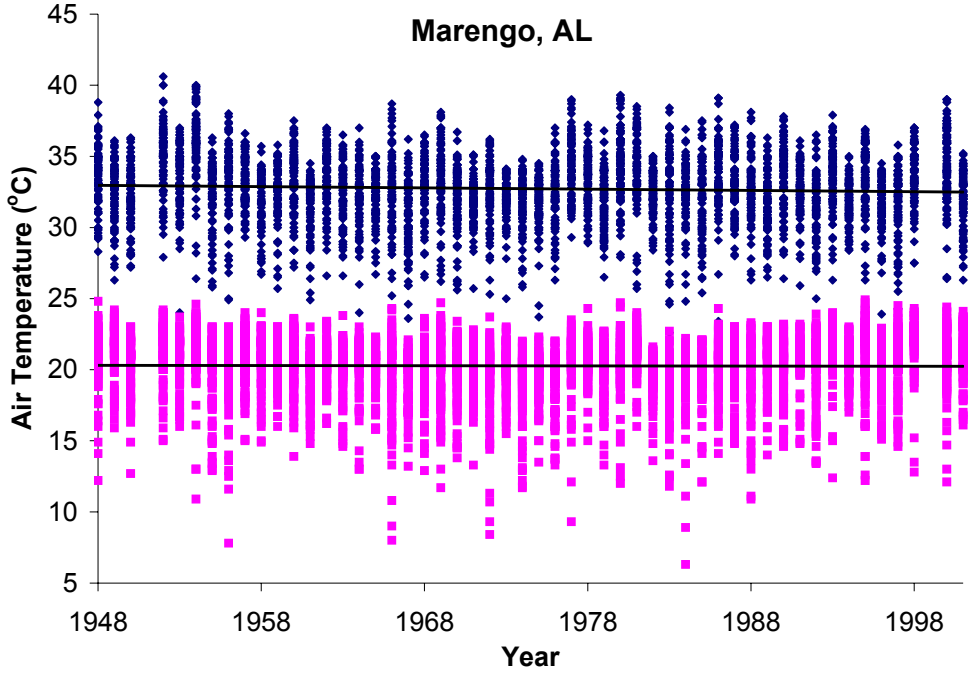


Figure B.3. Continued



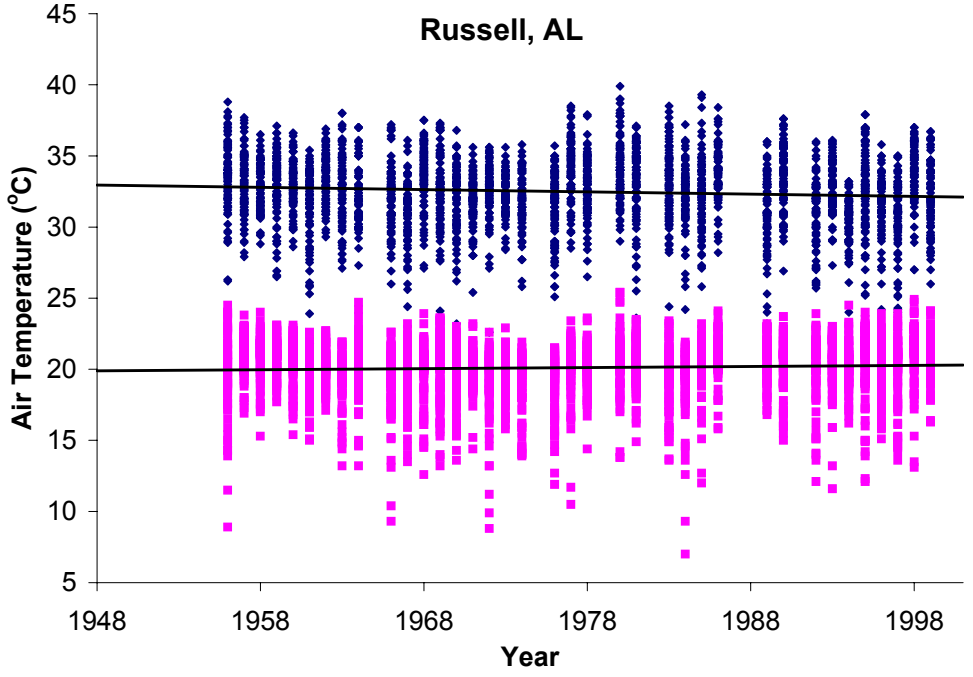


Figure B.3. Continued

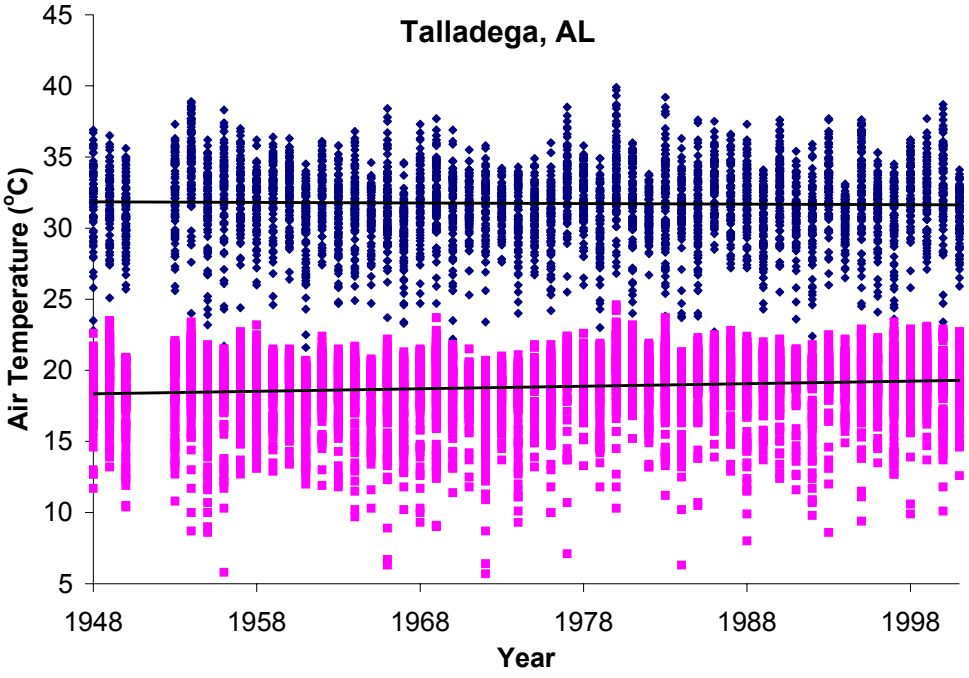


Figure B.3. Continued.

Maximum Temperature vs. Time		Slope	
High Forest Cover Group	Pearson's r	(^{o}C/year)	p-value
Choctaw, AL	-0.29	-0.02	
Appling, GA	0.20	0.01	0.15
Fairfield, SC	-0.14	-0.01	0.32
Jones, GA	-0.07	-0.01	0.62
Dawson, GA	0.06	0.01	0.73
Low Forest Cover Group			
Iredell, NC	-0.24	-0.01	
Morgan, AL	-0.21	-0.02	0.18
Barrow, GA	0.15	0.01	0.29
Orangeburg, SC	-0.06	-0.01	0.67
Lee, GA	-0.05	0.00	0.71
Medium Forest Cover Group			
Bartow, GA	-0.44	-0.04	
Butler, AL	-0.19	-0.01	0.18
Russell, AL	-0.22	-0.02	0.18
Chesterfield, SC	-0.21	-0.02	0.23
Greenwood, SC	-0.14	-0.01	0.34
Marengo, AL	-0.13	-0.01	0.35
Talladega, AL	-0.06	0.00	0.65
Lamar, AL	-0.04	0.00	0.78
Darlington, SC	-0.03	0.00	0.83

Appendix C

RESULTS FROM MULTIPLE LINEAR REGRESSION ANALYSIS

Three climate variables, mean daily maximum and minimum temperature, and presence/absence of precipitation were stratified by the four dominant summer air masses.[1] An analysis of variance (ANOVA) test was performed on these data using three independent variables: distance from the ocean (as measured from the center of the county group), elevation above sea level (the average elevation of the county group), and percent forest cover. The climate data were calculated according to the five-year average for each county group for each air mass. For example, one datum would be the average maximum daily temperature for the Appling County group from 1948 through 1952 for the DM air mass. The next datum would be for the period from 1953 through 1957 and so on. For the precipitation data, the average was calculated as the mean number of days with precipitation over a ten-day period during each five-year period for that air mass (e.g. for the MM air mass, values were often upwards of 7 or 8 days per 10-day period with precipitation). The following tables show the results of the multiple linear regression. The discussion of these results is found in Chapter 4.

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[1] The four air masses are the Dry Moderate (DM), Dry Tropical (DT), Moist Moderate (MM), and Moist Tropical (MT). See Chapter 3 for further explanation of the air mass typology.

Table C.1. Results of multiple linear regression for maximum daily temperature by air mass.

Dependent Variable	Model F	0.00	
DM Maximum Temperature	R-Squared	0.51	
	Independent Variables		
	Distance	Elevation	Percent Forest Cover
Coefficients	0.001	-0.008	-0.008
P-value	0.395	0.000	0.033

Dependent Variable	Model F	0.00	
DT Maximum Temperature	R-Squared	0.29	
	Independent Variables		
	Distance	Elevation	Percent Forest Cover
Coefficients	-0.001	-0.006	-0.027
P-value	0.685	0.001	0.000

Dependent Variable	Model F	0.00	
MM Maximum Temperature	R-Squared	0.66	
	Independent Variables		
	Distance	Elevation	Percent Forest Cover
Coefficients	0.002	-0.011	0.011
P-value	0.086	0.000	0.003

Dependent Variable	Model F	0.00	
MT Maximum Temperature	R-Squared	0.64	
	Independent Variables		
	Distance	Elevation	Percent Forest Cover
Coefficients	0.000	-0.008	-0.008
P-value	0.624	0.000	0.014

Table C.2. Same as Table C.1, except for minimum daily temperature.

Dependent Variable	Model F	0.00	
DM Minimum Temperature	R-Squared	0.51	
	Independent Variables		
	Distance	Elevation	Percent Forest Cover
Coefficients	-0.004	-0.005	-0.011
P-value	0.002	0.000	0.021

Dependent Variable	Model F	0.00	
DT Minimum Temperature	R-Squared	0.54	
	Independent Variables		
	Distance	Elevation	Percent Forest Cover
Coefficients	-0.006	-0.003	-0.025
P-value	0.000	0.014	0.000

Dependent Variable	Model F	0.00	
MM Minimum Temperature	R-Squared	0.74	
	Independent Variables		
	Distance	Elevation	Percent Forest Cover
Coefficients	-0.002	-0.005	-0.014
P-value	0.001	0.001	0.002

Dependent Variable	Model F	0.00	
MT Minimum Temperature	R-Squared	0.72	
	Independent Variables		
	Distance	Elevation	Percent Forest Cover
Coefficients	-0.003	-0.004	-0.017
P-value	0.000	0.000	0.000

Table C.3. Same as Table C.1, except for number of days with precipitation in a ten-day period.

Dependent Variable **DM Precipitation Frequency**	Model F	0.00	
	R-Squared	0.17	
	Independent Variables		
	Distance	Elevation	Percent Forest Cover
Coefficients	-0.001	-0.002	0.024
P-value	0.549	0.188	0.000

Dependent Variable **DT Precipitation Frequency**	Model F	0.11	
	R-Squared	0.02	
	Independent Variables		
	Distance	Elevation	Percent Forest Cover
Coefficients	-0.001	0.000	0.019
P-value	0.530	0.873	0.030

Dependent Variable **MM Precipitation Frequency**	Model F	0.00	
	R-Squared	0.07	
	Independent Variables		
	Distance	Elevation	Percent Forest Cover
Coefficients	-0.004	0.003	-0.010
P-value	0.000	0.005	0.017

Dependent Variable **MT Precipitation Frequency**	Model F	0.00	
	R-Squared	0.14	
	Independent Variables		
	Distance	Elevation	Percent Forest Cover
Coefficients	-0.007	0.007	-0.017
P-value	0.000	0.000	0.001

In the next group of figures the Dawson, GA county group was removed from the analysis. The county group's high elevation could cause spurious results because of its cool temperatures, high precipitation, and high forest cover (see Chapter 4 for further discussion). The new regression model explained less of the total variance in the data, which is too be expected given the large influence that the county group had on the original analysis.

Table C.4. Same as Table C.1 except without Dawson, GA county group in analysis.

Dependent Variable **DM Maximum Temperature** (without Dawson, GA group)	Model F	0.00	
	R-Squared	0.21	
	Independent Variables		
	Distance	Elevation	Percent Forest Cover
Coefficients	-0.001	-0.005	-0.005
P-value	0.584	0.008	0.176

Dependent Variable **DT Maximum Temperature** (without Dawson, GA group)	Model F	0.00	
	R-Squared	0.11	
	Independent Variables		
	Distance	Elevation	Percent Forest Cover
Coefficients	-0.003	-0.002	-0.025
P-value	0.209	0.628	0.001

Dependent Variable **MM Maximum Temperature** (without Dawson, GA group)	Model F	0.00	
	R-Squared	0.49	
	Independent Variables		
	Distance	Elevation	Percent Forest Cover
Coefficients	0.002	-0.012	0.010
P-value	0.070	0.000	0.013

Dependent Variable **MT Maximum Temperature** (without Dawson, GA group)	Model F	0.00	
	R-Squared	0.34	
	Independent Variables		
	Distance	Elevation	Percent Forest Cover
Coefficients	-0.001	-0.005	-0.005
P-value	0.186	0.002	0.150

Table C.5. Same as Table C.4 except for minimum daily temperature.

Dependent Variable	Model F	0.00	
DM Minimum Temperature	R-Squared	0.37	
(without Dawson, GA group)			
	Independent Variables		
	Distance	Elevation	Percent Forest Cover
Coefficients	-0.004	-0.006	-0.011
P-value	0.024	0.011	0.027

Dependent Variable	Model F	0.00	
DT Minimum Temperature	R-Squared	0.41	
(without Dawson, GA group)			
	Independent Variables		
	Distance	Elevation	Percent Forest Cover
Coefficients	-0.006	-0.003	-0.023
P-value	0.000	0.258	0.000

Dependent Variable	Model F	0.00	
MM Minimum Temperature	R-Squared	0.56	
(without Dawson, GA group)			
	Independent Variables		
	Distance	Elevation	Percent Forest Cover
Coefficients	-0.003	-0.004	-0.013
P-value	0.000	0.001	0.000

Dependent Variable	Model F	0.00	
MT Minimum Temperature	R-Squared	0.56	
(without Dawson, GA group)			
	Independent Variables		
	Distance	Elevation	Percent Forest Cover
Coefficients	-0.004	-0.003	-0.016
P-value	0.000	0.011	0.000

Table C.6. Same as Table C.4 except for number of days with precipitation in a ten-day period.

Dependent Variable **DM Precipitation Frequency** (without Dawson, GA group)	Model F	0.00	
	R-Squared	0.18	
	Independent Variables		
	Distance	Elevation	Percent Forest Cover
Coefficients	0.001	-0.005	0.021
P-value	0.665	0.044	0.000

Dependent Variable **DT Precipitation Frequency** (without Dawson, GA group)	Model F	0.08	
	R-Squared	0.02	
	Independent Variables		
	Distance	Elevation	Percent Forest Cover
Coefficients	-0.002	0.001	0.020
P-value	0.542	0.848	0.030

Dependent Variable **MM Precipitation Frequency** (without Dawson, GA group)	Model F	0.00	
	R-Squared	0.07	
	Independent Variables		
	Distance	Elevation	Percent Forest Cover
Coefficients	-0.005	0.004	-0.009
P-value	0.001	0.028	0.042

Dependent Variable **MT Precipitation Frequency** (without Dawson, GA group)	Model F	0.00	
	R-Squared	0.20	
	Independent Variables		
	Distance	Elevation	Percent Forest Cover
Coefficients	-0.001	0.014	-0.011
P-value	0.000	0.000	0.042

Appendix D

CALCULATION OF THE TEST STATISTICS

D.1 Coefficient of Variability

One of the more common statistics to calculate when climatic data are involved is the coefficient of variability (CV). The CV is the standard deviation expressed relative to the magnitude of the mean (McGrew and Monroe, 1993) and is given as:

$$CV = \frac{s}{\overline{X}} \quad \text{or} \quad CV = \frac{s}{\overline{X}} \cdot 100 \qquad \text{(D.1)}$$

where s is the standard deviation of the population or sample and $\overline{X}$ is the mean. The main advantage of the CV is it provides a simple way to measure differences in variability across geographic regions by determining the relative variability experienced in each place.

D.2 Kolmogorov-Smirnov Test

In the KS Test, relative cumulative frequencies are compared between groups. The absolute value of the difference between each corresponding frequency value is determined and the largest difference *D* is compared to the critical value of D

to determine significance. Since all of the samples are large, the critical value of D is given by:

$$D = \frac{c(\alpha)}{\sqrt{N}} \qquad \text{(D.2)}$$

where D is the critical value to test for statistical significance, c is a constant determined by the α level (in this case $c = 1.63$ for an α level of 0.01 or 1.22 for an α level of 0.1), and N is the sample size (Massey 1951).

D.3 Calculation of Gamma Distribution Parameters

Gamma functions were fit to the pooled data of all county groups or station data in each of the tests in Section 4.6 to test for significant differences between groups. Data were fit according to the maximum likelihood estimators as outlined by Thom (1958). Pooling the data across geographic regions was justified according to a 3-step process:

1. A gamma distribution provides the best fit for individual station (or county group) data.
2. There is no difference between an interpolated gamma function for a county group and a gamma function for a county group derived from pooled data.
3. Pooled data from all county groups are not different from the individual county group data.

To illustrate how the gamma functions were estimated consider the first test in Section 4.6 comparing differences in precipitation events. Since interpolated precipitation data averaged over county groups are not appropriate for this comparison, the raw station data were compared. But before the station data could be pooled into a low forest cover group (LFCG) and a high forest cover group (HFCG), it was necessary check that a gamma function is the best fit for the daily precipitation data. An example of one such gamma fit is seen in Figure D.1. Here the empirical distribution function (EDF) from an individual station in the Jones, GA group in the HFCG is overlaid with the fitted gamma distribution. The KS-test was used to measure the goodness-of-fit of the gamma function and indicated that the observed and estimated distribution were not significantly different ($D = 0.04$, critical $D = 0.28$ at α level of 0.01).

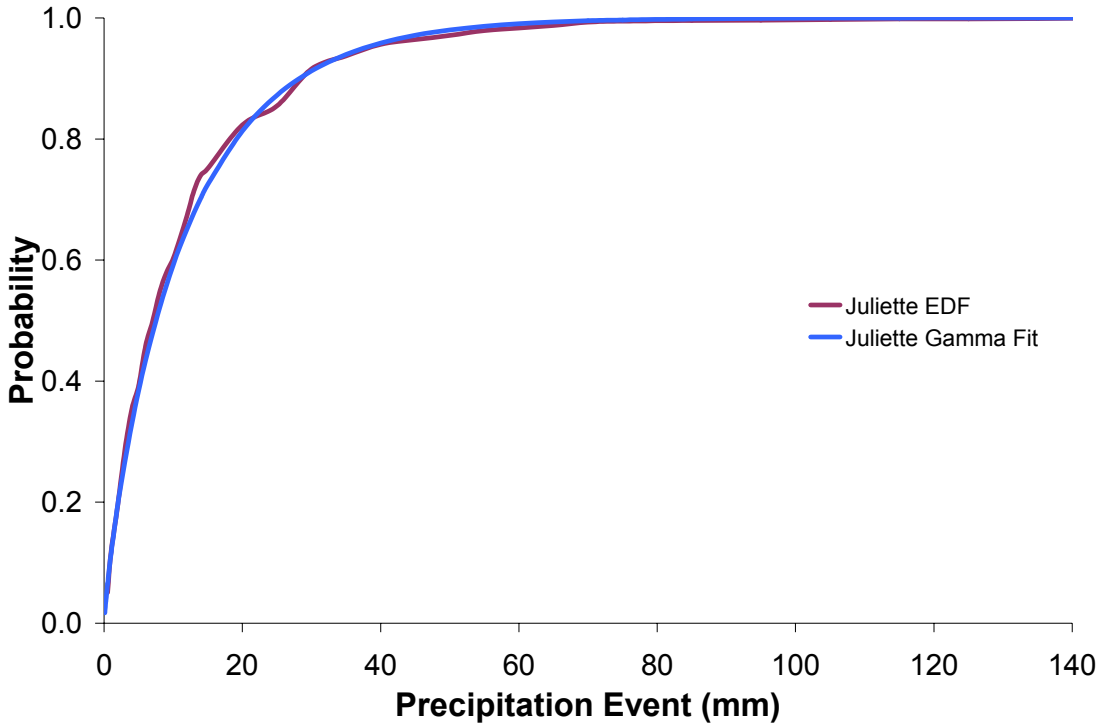


Figure D.1. EDF for an individual station in the Jones, GA county group and the estimated gamma distribution for the station as calculated by the maximum likelihood method (see Thom 1958).

Step two determines if a gamma distribution can be estimated from all station data in a county group. The alternative is to determine the gamma function for each individual station and then interpolate the function's parameters (α,β) to a grid of the county group. The county group's gamma function parameters are calculated from the average of the grid cell values. This step also showed that pooling the data together was an appropriate way to analyze the differences between the forest cover groups. To wit, Figure D.2 examines the difference between the two methods when calculating the gamma distribution for the Appling, GA group in the HFCG. The

probability curves are very similar to each other and accordingly the KS-test showed no significant differences between the interpolated gamma function and the pooled gamma function (D = 0.04, critical D = 0.28 at α level of 0.01).

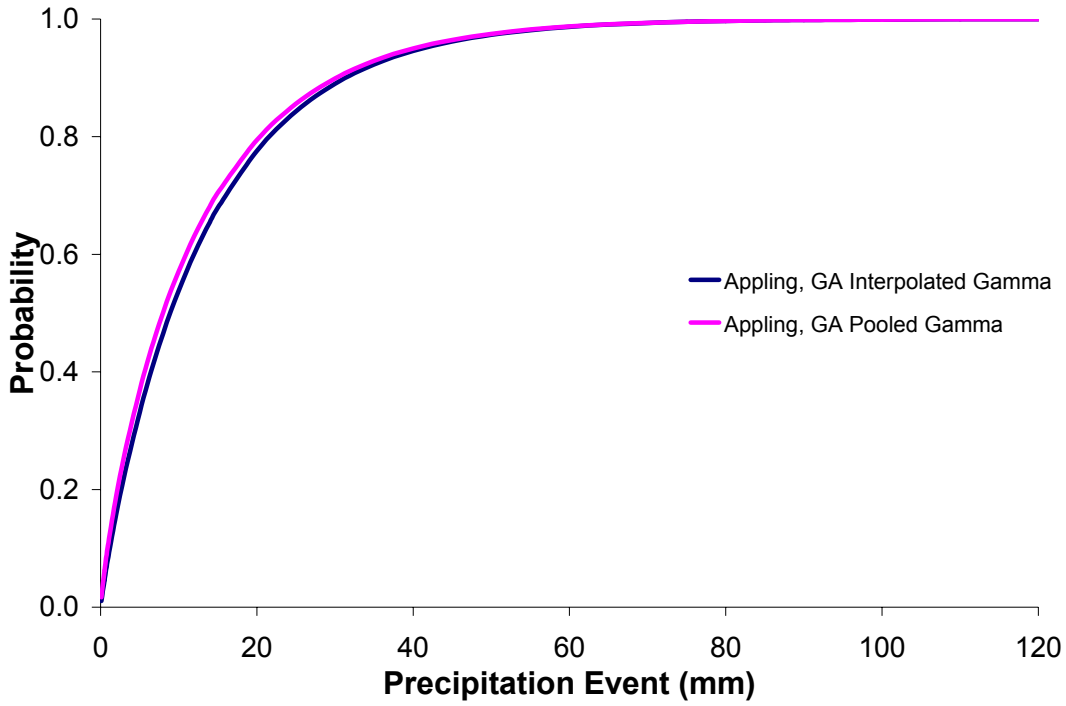


Figure D.2. Appling, GA gamma distributions describing daily precipitation event probability. Distributions were calculated from averaged interpolated gamma function parameters (blue), or from pooled station data (pink).

The final step compared the pooled station data over all county groups in a forest cover group to the pooled data in each individual county group. For the LFCG (and HFCG) this means using the KS-test to make sure there are no significant differences between the estimated gamma distribution for the LFCG (or HFCG) and any of the estimated gamma distributions for the county groups. The results showed no significant differences between any of the county group gamma functions and the pooled gamma functions for the entire LFCG and HFCG (Table D.1).

Table D.1. Results of KS-test comparison of gamma parameters for individual versus pooled county groups.

County Group	Gamma Alpha	Gamma Beta	KS-Test (critical D = 0.28)
Appling, GA	0.828	15.1	0.00
Choctaw, AL	0.864	14.9	0.02
Fairfield, SC	0.798	15.3	0.01
Jones, GA	0.834	14.3	0.01
Pooled HFCG	0.833	14.9	
Barrow, GA	0.748	14.7	0.02
Iredell, NC	0.765	14.1	0.02
Lee, GA	0.806	14.7	0.02
Morgan, AL	0.802	14.6	0.01
Pooled LFCG	0.782	14.5	

Appendix E

EVALUATION OF SPATIAL BIAS

E.1 Effect of Geographic Location

As seen in Figure 4.1 at the beginning of Chapter 4, there are two high forest cover county groups that lie within the coastal plain (Appling, GA and Choctaw, AL), compared to only one low forest cover county group (Lee, GA).[1] Because precipitation generally increases from the central piedmont towards the coast, it is important to verify that the additional coastal plain county group in the high forest cover group (HFCG) is not biasing the results towards more frequent precipitation events solely because of proximity to the ocean. To accomplish this, a precipitation ogive was created for the high forest cover group without the Choctaw county group and then compared to both the original HFCG and the low forest cover group (LFCG). An inspection of the three ogives in Figure E.1 shows that the new ogive without the Choctaw, AL group is nearly identical to the original high forest cover ogive that contained all four county groups. A close-up of the main area of difference between the LFCG and HFCG (Figure E.1b) confirms that the ogive for the new Choctaw-less group is almost identical to the original high forest cover group. The results of the K-

[1] Initially there were two county groups with low forest cover in the coastal plain (Lee, GA and Orangeburg, SC). However, the Orangeburg county group was removed from the high forest cover group before any analysis was performed so only one county group remains.

S test also confirmed that the Choctaw-less county groups were not significantly different from the original high forest cover group (D = 0.00, Critical D = 0.01 at α = 0.10 level).

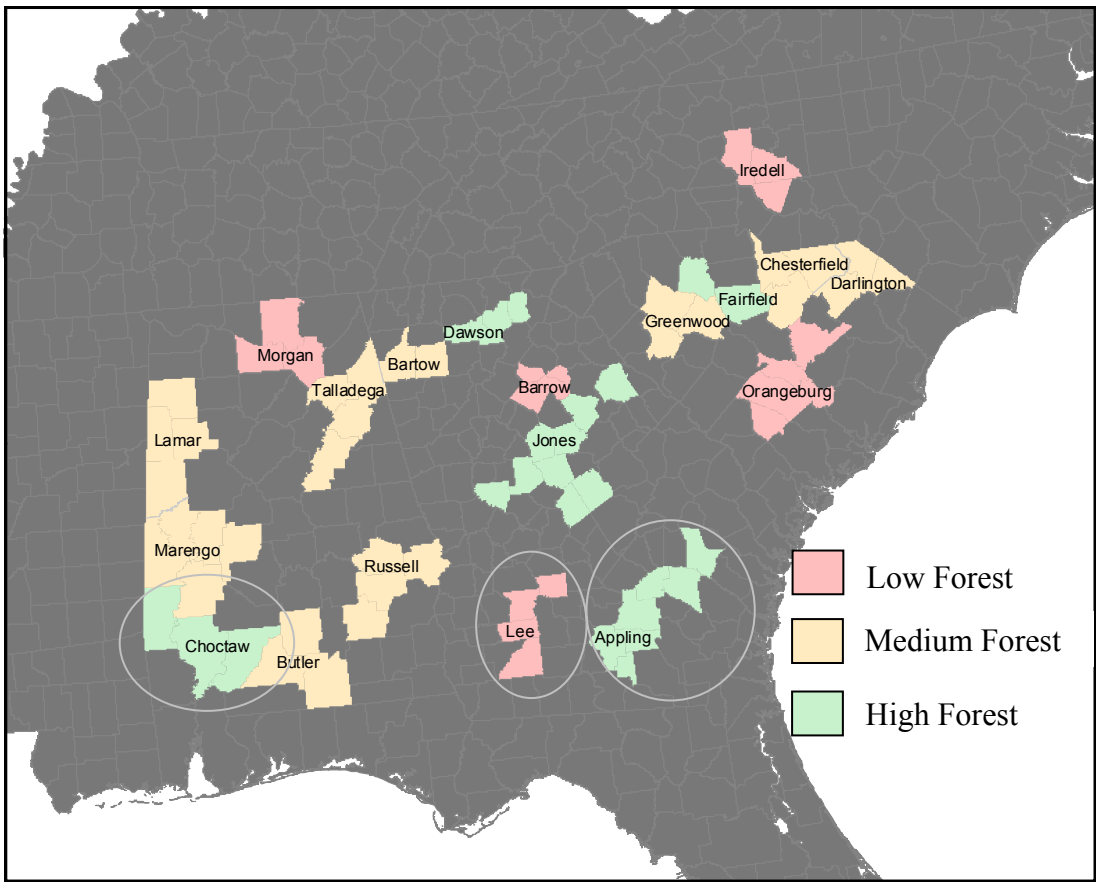
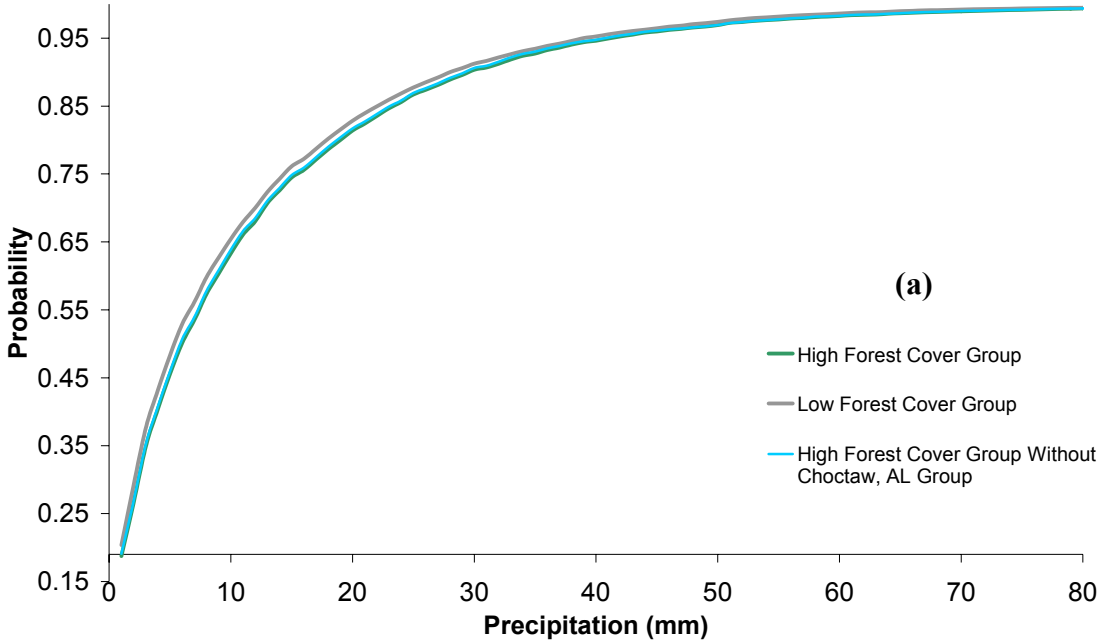


Figure E.1. Location of county groups that were created from the methods described in Chapter 3. Circled county groups indicate groups used in the soil moisture analysis that have some portion of their area inside the coastal plain.



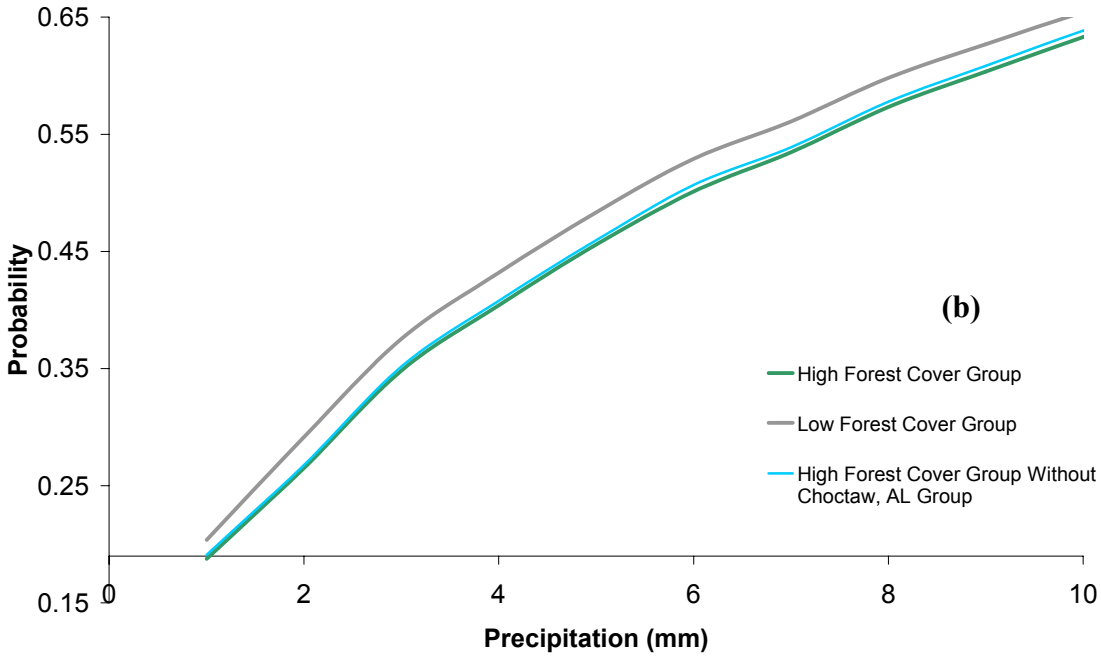


Figure E.2. Same as Figure 4.6 except for the inclusion of the high forest cover group without the Choctaw, AL group **(a)**, and a close-up view of the area of significant difference between the HFCG and LFCG **(b)**.

Figure E.3. further explores the influence of geography on the precipitation analysis. As in Figure E.2b, the data are shown for precipitation events of 10 mm or less. But in this figure all of the county groups are separated out into their individual ogive curves. Each county group represents the cumulative frequency of precipitation events for all stations in the county group (see Chapter 3 for further explanation). And once again, for the most part all of the low forest cover groups had more instances of lower amounts of precipitation than the high forest cover groups. The only consistent exception to this was the Lee, GA group. This is because its location in southern Georgia is closer to the two major sources of moisture in the summer months (the Gulf of Mexico, and the Atlantic Ocean).

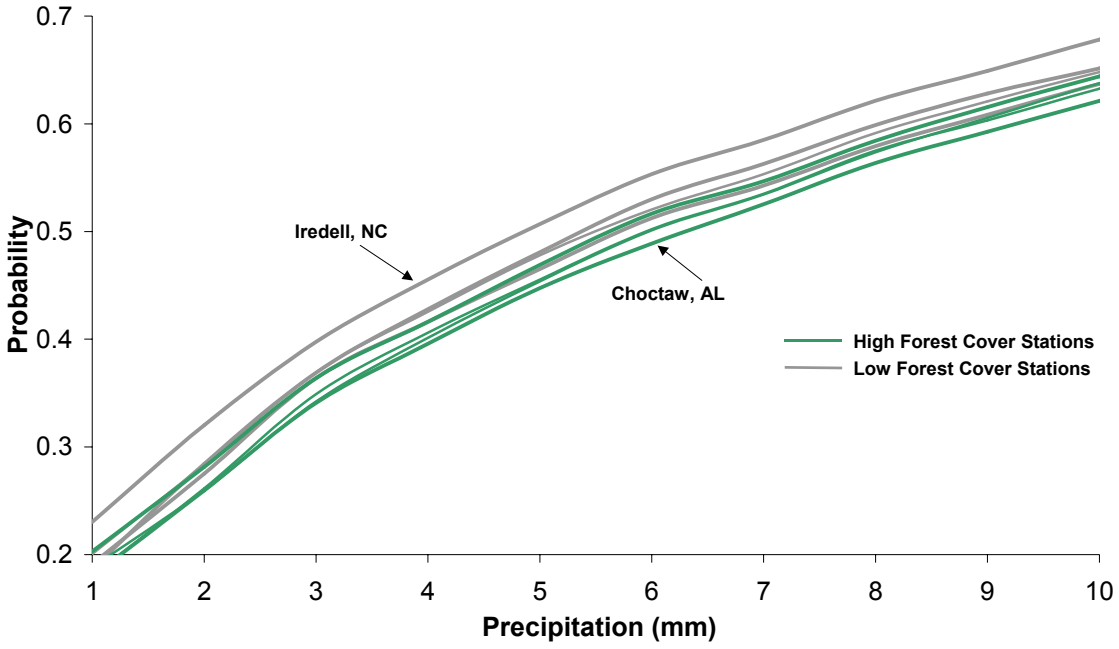


Figure E.3. Ogive curves of precipitation events for individual county groups.

E.2 Effect of Field Capacity

Figure 4.10 shows the size of the precipitation event that raised soil moisture above 35% of field capacity. The differences were not statistically significant but were not non-negligible either. However, even this small difference may be due to disparities in field capacities between the two forest cover groups. The four county groups in the HFCG have an average field capacity of 2.8 inches (for a two foot rooting depth).[2] In contrast, the four county groups in the LFCG have an average field capacity of 3.1 inches down to the two-foot rooting depth. With a difference of 10% between the two groups, it can be expected that a lower field capacity by itself would have an impact on the amount of precipitation required to increase soil moisture above 35%. To test this, the county group with the lowest field capacity[3] was removed from the HFCG in a similar way as in Section E.1. After its removal, the new average field capacity for the HFCG was now 3.1 inches for the two-foot rooting depth (the same as the LFCG). New gamma functions were estimated from the new HFCG and compared to the LFCG (Figure E.4). There is a slight shift towards larger precipitation events to surpass the 35% thresholds in the HFCG (that is, the new probability curve is closer to the low forest cover probability curve). But since the original test's results were not statistically significant, it is not surprising that the new results were not statistically significant at the 0.1 alpha level (D = 0.08, critical D = 0.21). However, the pattern is still the same, and the overall

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[2] Inches are used as the unit of measurement here in accordance with the common practices of U.S. soil scientists.

[3] The Appling, GA group had the lowest field capacity in the HFCG. Its field capacity of 2.1 inches for the two-foot rooting depth was the lowest of all county groups for both groups.

difference between the original high forest cover curve is small. Therefore, field capacity is not influencing the results of these tests.

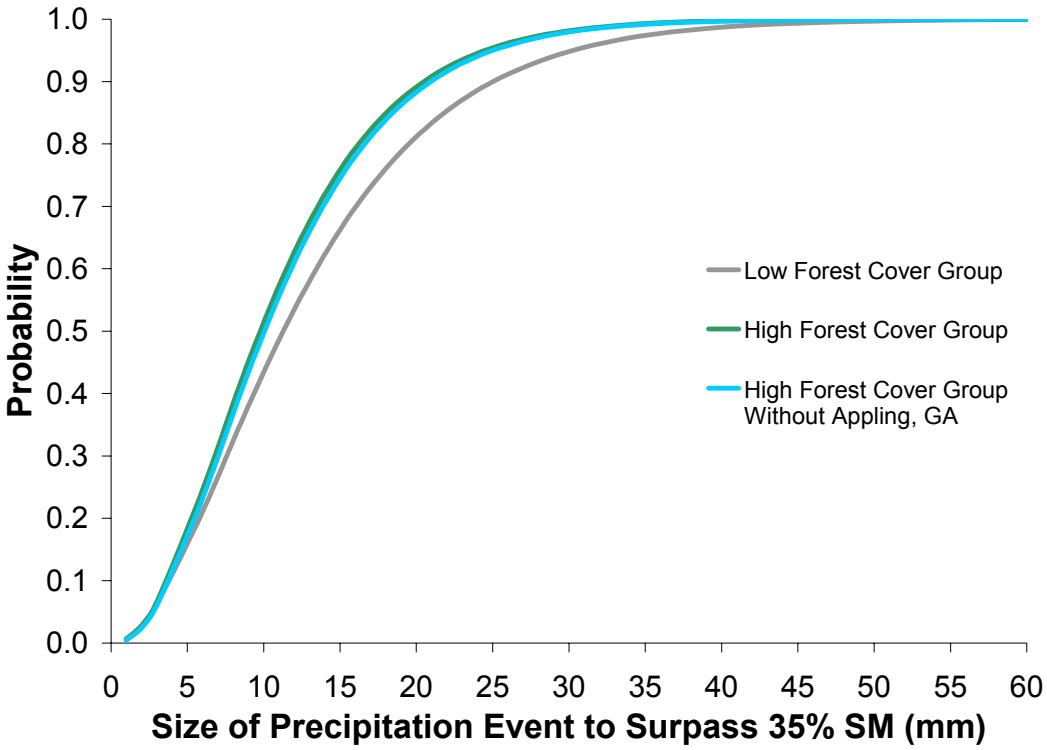

Figure E.4. Same as Figure 4.10 except that the additional gamma function represents the HFCG without the county group with the lowest field capacity.

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