Assessment of Control Charts for Evaluating Dynamic Accuracy of Forest Growth Models

Richard Raymond Cristan

University of Tennessee - Knoxville, rcristan3@gmail.com

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To the Graduate Council:

I am submitting herewith a thesis written by Richard Raymond Cristan entitled "Assessment of Control Charts for Evaluating Dynamic Accuracy of Forest Growth Models." I have examined the final electronic copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Forestry.

Jason Henning, Major Professor

We have read this thesis and recommend its acceptance:

John Coulston, Donald Hodges

Accepted for the Council:

Carolyn R. Hodges

Vice Provost and Dean of the Graduate School

(Original signatures are on file with official student records.)
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Assessment of Control Charts for Evaluating Dynamic Accuracy of Forest Growth Models

A Thesis
Presented for the
Master of Science Degree
The University of Tennessee, Knoxville

Richard Raymond Cristan
December 2010
Abstract
The purpose of this study was to determine if control charts are an effective tool to identify trends in forest growth and yield model accuracy. Accurate forest growth and yield models are important for projecting future forest composition. However, environmental factors have the potential to make forest growth models created from historic data inaccurate. Control charts in this study determine if forest growth predictions fall within confidence limits established for historic growth at a number of points in time. Two data sets were used in this study: the first was a Continuous Forest Inventory (CFI) from three tracts at the University of Tennessee Cumberland Research Station and the second data set was Forest Inventory and Analysis data collected by the U.S. Forest Service. The CFI plots represented a stand level data set measured every 5 years from 1962-1977 and revisited for a re-measurement in 2009. The FIA plots were a regional data with subsets of plots measured annually from 1999-2008. The FIA data set was limited to plots of the oak/hickory forest type from Tennessee, Alabama, and Georgia. Two forest growth and yield models were used to predict growth: (1) WinYield and (2) Forest Vegetation Simulator (FVS). The two different data sets were used with both FVS and WinYield to evaluate control charts using different models ad at different spatial and temporal scales. The data sets were also subset by site index, stand age, stocking percent, aspect, and species composition to determine if control charts could identify changes in model accuracy for forests subjected to different growing conditions. The CFI and FIA data had short growth predictions and control charts indicated that there were no trends affecting accuracy. The CFI data also had a long growth prediction of 32 years and the control charts found that the predictions using WinYield and FVS were inaccurate, indicating that there may be a trend causing inaccuracy in the model.
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Introduction
Forest management for the production of timber and other forest products depends on the quantity and quality of growing stock. Growth determination is essential for forest management and planning. Inadequate knowledge can result in overcutting or undercutting. Management of forests depends on present and predicted information about the forest. Predictions about the future state of forest stands are typically made with growth and yield models. Consequently, the accuracy of growth and yield models can directly affect how well forest resources are managed. Evaluation of these models is necessary to build confidence in their predictions (Vanclay and Skovsgaard 1997)

Forest growth modeling
Forest growth and yield research started in the 1850’s when graphical methods were used to model growth and production of European forests (Vuokila 1965). German researchers in the 1860’s and 1870’s installed long-term forest yield experiment plots. They measured yield as the net wood volume produced by the forest. The first yield tables created by European researchers included complete observations of yield and involved entire rotations for important tree species (Peng 2000). These yield tables were formulated for single species stands until the 1930’s when investigations were expanded to mixed species stands (Pretzsch 2009). American yield tables at this time were based on stand age, site index, and tree height (Monserud 1984) and were used until the 1950’s when modeling efforts expanded with advances in technology and mathematical statistics (Peng 2000). Moser and Hall (1969) developed growth and yield functions for un-even aged forests from permanent plot data. By 1973, forest growth software programs for computers were beginning to be researched (Bruce and Wensel 1987).
Functions to model forest growth and yield were typically created using data from repeatedly measured plots. Growth functions were generally created by modeling measured growth over a time period based variables such as tree species, tree size, competition, site quality, and age. Once the growth functions were formed, computer software programs could incorporate the functions to predict the future growth and estimate the yield of a forest stand. Growth and yield models can consist of a single equation or a series of interrelated sub-models (Peng 2000).

Growth and yield models can be broadly categorized as stand level or individual tree. Stand level models require stand variables such as basal area density, volume density, or a diameter distribution as inputs representing initial conditions (Peng 2000). Stand level models can not provide predictions for individual tree growth but usually require relatively little input information to project stand growth (Peng 2000). These models are most effective for single species even-aged stands and have limited use for mixed species stands where species interactions and size distributions are difficult to model using stand level variables (Ritchie 1999).

The first individual tree model was developed by Newham in 1963 for pure Douglas fir stands (Newnham 1964). Ek and Monserud in the 1970’s introduced individual tree growth models for pure un-evenaged and mixed species stands (Ek and Monserud 1974). Individual tree models provide detailed information about stand dynamics and structure. They also include distributions of stand volume by tree size classes (Avery and Burkhart 2002). The main element of this type of model was typically a system of equations that modeled the growth of individual trees in relation to site factors (Pretzsch 2009). Example site factors are stand age, site index, species composition, and climate.
Individual tree models can be further categorized into two types: distance independent and distance dependent. Avery and Burkhart (2002) list three basic components of individual tree models: (1) a diameter-growth component, (2) a height growth component, and (3) a mortality component. Distance independent models project tree growth by size classes or individually and do not require individual tree location coordinates (Avery and Burkhart 2002). Stand data such as stand age and site index are required for most distance-independent models. The Prognosis model developed by Stage (1973) and Wykoff et al. (1982) is one of a few distance-independent models that does not require age or site index. Prognosis was the historical basis of the USDA Forest Service’s growth and yield model the Forest Vegetation Simulator (FVS).

Distance-dependent models differ in overall concept. The initial stand conditions are required for each tree along with coordinates representing that tree’s location (Avery and Burkhart 2002). Individual tree diameter, height, crown ratio, and crown diameter are also typically required. An individual tree’s predicted growth is limited by the locations and relative sizes of competing trees (Peng 2000). These models were developed in an effort to evaluate competition between trees. They can provide more detailed information about tree and stand development and include relationships expressing biological and ecological interactions (Peng 2000). One example of a distance-dependent model is FOREST created by Ek and Monserud (1974). It was designed to predict growth and regeneration of both even-aged and uneven-aged mixed species stands of northern hardwoods (Peng 2000). The input variables needed to run FOREST are individual tree location coordinates, height, diameter, age, clear bole length, and species. Individual tree distance independent models are expensive to develop and implement because individual tree
coordinates are not commonly available and are labor intensive to measure (Ek and Monsrud 1974).

Some alternatives to growth and yield models include process and hybrid models which are currently being studied for forest management and monitoring. Process models typically use carbon balance estimates of photosynthetic production under which tree growth can be examined (Makela et al. 2000). Results from carbon balance models do not readily convert to basal area and diameter growth predictions commonly used in forest management (Korzukhin et al. 1996; Johnsen et al. 2001). Some process models also were created to monitor forest health (Blake et al. 1990). Some researchers tried to measure the growth of tree and stand components as influenced by environmental factors then predict how future growth would change due to changes in the environment (Blake et al. 1990). Hybrid models have been developed that combine growth and yield models with process models to help predict growth under a changing environment (Peng 2000). Hybrid models have also been used to test the sensitivity of growth and yield models to environmental variability (Battaglia and Sands 1998). Existing hybrid models include a limited number of input variables, making it difficult to account for the full range of environmental factors that may affect forest growth (Battaglia and Sands 1998).

Distance independent, stand level and individual tree, growth and yield models remain the most common tools used by forest managers to predict growth, schedule management activities, and evaluate proposed treatments (Peng 2000). The data necessary to employ such models are routinely collected in forest inventories and the outputs are detailed enough to support evaluation of management strategies and estimate future production (Peng 2000).
Growth and yield model accuracy
Predicting timber value and volume for the future is a key application of growth and yield models. Inaccurate timber value and volume prediction can be costly to landowners, timber management companies, and foresters as well as negatively impacting the use of forest resources and overall forest health. If a forest manager projects the wrong growth and yield it could result in harvesting too early or late. This could decrease profits for landowners. Future stand composition is affected by harvesting and if a harvest is done at the wrong time or wrong intensity, regeneration of the stand could result in undesirable species composition.

Growth and yield models may become inaccurate over time due to the influence of climate and environmental variability (Henning and Burk 2004). This is because growth and yield models predict future growth assuming it will be similar to historic growth. Growth and yield models are fit to data from forests grown under historic conditions. If the forest environment and growing conditions change over time, growth and yield models developed with historic data may become inaccurate. Ecosystems and forest environments may change due to factors such as climate change, disease, invasive species, and the introduction of new insects or pathogens. Long-term trends in forest management policy such as fire suppression can also cause future forest development to deviate from historic trends. It is difficult to predict when an environmental factor or a combination of environmental factors is going to cause forest growth to deviate from historic averages. Models may become inaccurate over time due to environmental factors or from deficiencies in the equation used in the forest growth and yield model.

Predicted global and regional climate change associated with increasing atmospheric CO₂ and other greenhouse gases have been shown to impact precipitation and temperature subsequently
influencing ecosystem water budgets (Hanson and Wullschleger 2006). Changes in precipitation are expected to alter surface evaporation, transpiration, and soil water content, which will impact plant functions, including altering tree growth (Hanson and Wullschleger 2006). Trees respond to water stress by suppressing photosynthesis to avoid water loss through transpiration, thereby inhibiting growth (Slatyer 1967). Increases in temperature are also expected to intensify the rate of hydrologic cycling at regional and global scales (Houghton et al. 2001). This may result in an increase in the number of hot days and a reduction in cold days, along with changes in the intensity and frequency of floods and droughts.

This study will focus on southern hardwood forests of Tennessee, Alabama, and Georgia. Part of the study will look at all the states together from 1999-2008 and the other part will just include Tennessee from 1962-2009. The average annual rainfall for all three states was 51.93 inches (Figure 1). From 1999-2001 and 2005-2007 the average annual rainfall was below average, with 2007 being the lowest at 33 inches. Annual rainfall for Tennessee averages 49 inches (Figure 2). The only prolonged period of low precipitation in Tennessee occurred in the late 1980’s with 4 straight years of 39 inches. The lowest annual rainfall occurred in 2007 at 34 inches. Rainfall fluctuated annually, but years of excessive rainfall or droughts may cause changes in forest growth (Colbert et al. 2002).

Atmospheric CO₂ and tropospheric ozone (O₃) levels have been rising and can have effects on forest production (King et al. 2005). Rising tropospheric ozone (O₃) levels can cause forest production to decrease (King et al. 2005). Forest growth responds positively to carbon sequestration and rising CO₂, but with O₃ rising, all of the gains are lost (King et al. 2005). Nitrogen (N) deposition has been another factor shown to affect tree growth (Boggs et al. 2005).
Deciduous forests in the eastern United States have been N limited, so the addition of N caused trees to respond with increased growth rates (Boggs et al. 2005). Forests tend to retain N through internal cycling while N losses through leaching of nitrates and de-nitrification have been shown to be relatively small (Gundersen 1991). Gundersen (1991) showed that the increase in atmospheric N deposition, forests are becoming N saturated causing an increase in nutrient leaching and soil acidification. Recently, lower elevation deciduous forests have shown negative health impacts and N deposition has been proposed as a source of these negative impacts (Boggs et al. 2005). The early stages of N deposition acts like a fertilizer for trees and when the forest becomes N saturated, it could have a negative effect on growth (Boggs et al. 2005).
Figure 1. Annual precipitation for Tennessee Alabama and Georgia from 1998-2009 with the average annual precipitation of all three states indicated at 51 inches. (ftp.ncdc.noaa.gov)
Figure 2. Tennessee annual precipitation from 1960-2009 with the average annual precipitation indicated at 49 inches. (ftp.ncdc.noaa.gov)
**Model evaluation**
Rykiel (1996) identified three types of model evaluation techniques: operational validation, theoretical validation, and data validation. A model that had been validated is considered acceptable for its intended use (Rykiel 1996). Operational validation demonstrates that model output meets the performance standards required for the models stated purpose. Theoretical or conceptual validations indicate that the assumptions, theories, and structure underlying the model are acceptable for its intended use. Data validation tests whether the data accurately represents the model (Rykiel 1996).

Operational validation was used in this study to test whether forest growth and yield model predictions agree with measured tree growth. This model evaluation technique was selected because forest growth and yield predictions are used to make forest management decisions. This validation technique typically tests the model outputs using hypothesis testing and confidence interval estimation (Rykiel 1996; Rauscher and Young 2000). Rauscher and Young (2000) used confidence interval estimation in testing the accuracy of growth and yield models because it was more practical than hypothesis testing. In their study, they tested the accuracy of basal area growth and stand density predictions for ten growth and yield models for Southern Appalachian and bottomland hardwood forests. One of the models they used was SETWIGS, which was developed by the USDA Forest Service and was part of the Southern variant of the Forest Vegetation Simulator (Dixon 2002).

Confidence interval estimation techniques have been a common tool of process control and they monitor a process over time. The process in this study was the prediction of forest growth by growth and yield models. Control charts were developed as a process control diagnostic. Control
charts can be used to monitor mean and standard deviation and were used here to evaluate model accuracy over time (Chandra 2001). Control charts help evaluate variability in data overtime.

This study looked into the effects of variation from site index, stand age, aspect, stocking percent, and dynamic model accuracy. Control charts determine if a model has been in a state of statistical control by examining past data (Ryan 2000). Statistical control is defined as the stability and predictability of a process over time (Benneyan 1998). For a process to be in statistical control it would have to be within the model confidence limits and if it fall outside, it would be considered statistically out of control (Benneyan 1998). Benneyan (1998) found control charts make it easy to indentify when a process goes out of control. Control charts are valuable for: (1) testing for and establishing a state of statistical control; (2) monitoring an in-control process for changes in process and outcome; (3) identifying, testing, and verifying process improvement opportunities.

**Forest growth models used**

Forest growth and yield models can be used to evaluate dynamic accuracy of growth over time.

Two commonly used growth and yield models in the southern United States include the Forest Vegetation Simulator (FVS) and WinYield (Hepp 1994). The Forest Vegetation Simulator was a growth projection tool developed by the United States Forest Service and has 22 different variants for all forested regions of the United States and part of British Columbia, Canada (Crookston and Dixon 2005). The southeast variant of FVS was developed in 1996 using relationships first included in the SETWIGS model (Donnelly et al. 2001). The SETWIGS model was parameterized for Alabama, Georgia, and South Carolina. The Southern Variant of FVS was developed in 1998 and released in 2001. This release included new growth equations derived from Forest Inventory and Analysis data and expanded to cover all of the southern states.
(Donnelly et al. 2001). The Forest Vegetation Simulator included sub-models that allowed for its use beyond growth and yield applications to large-scale assessments, forest health, forest planning, policy, resource supply analysis, climate change, forestry research, and teaching (Donnelly et al. 2001).

The Forest Vegetation Simulator was a distance independent, individual tree growth and yield simulator. The FVS model predicted diameter growth, height growth, and mortality. The input variables for FVS included: species, dbh, height, site index, forest type, and number of subplots considered forested and non-forested. The model can use inventory data and site information to calibrate the growth sub models to match input growth rates (Crookston and Dixon 2005).

Outputs of FVS included predicted stand conditions, sampling statistics, and calibration results. The output stand conditions included basal area growth and trees per acre. Prediction periods could range from every year to several hundred years. Stand development in FVS was simulated by aggregating predicted changes in the dimensions of trees in the input inventory and expanding these to stand level estimates. For trees greater than 5 inches dbh, diameter growth was predicted first then height growth was predicted as a function of diameter growth and other variables. For trees less than 5 inches dbh, height growth was predicted first and diameter growth was predicted as a function of height growth and other variables (Dixon 2002). There were two types of mortality models used in FVS: (1) background mortality, which accounted for occasional tree mortality when stand density was below a specified level and (2) density related mortality, which determined mortality rates for individual tree’s based on the trees relationship with the stand’s maximum potential density (USDA 2008). In-growth was calculated through the partial establishment model in FVS (USDA 2008).
Another commonly used growth and yield model in Tennessee was WinYield. The full WinYield model included tools for financial and tax planning although this research was only concerned with the forest growth component (Dangerfield and Moorhead 1998). The WinYield growth model has been used by consultant foresters and industry and state foresters to predict future stand conditions and perform financial analysis for landowners (Dangerfield and Moorhead 1998). The WinYield model included separate growth equations for each of 14 major timber types of the Southern United States (Dangerfield and Moorhead 1998). WinYield was developed by Hepp in 1994 at the Tennessee Valley Authority (Dangerfield and Moorhead 1998). The growth model for upland oak forests in WinYield was developed by Dale (1972) from research plots in Kentucky, Ohio, Missouri, and Iowa. The inputs for WinYield included: rotation length, site index, log rule for volume estimates, stand age, diameter, and height. Outputs included summaries of basal area and volume yields.

**Objectives**

A key challenge in the application of growth and yield models has been to determine when a model fails to give predictions that are accurate enough to be the basis of forest management decisions.

The objectives of this study are to:

1. Evaluate control charts as a tool to diagnose trends in growth and yield model accuracy;
2. Evaluate the utility of control charts at different spatial and temporal scales for evaluating growth and yield model accuracy;
This study examined the utility of control charts in evaluating FVS and WinYield as representatives of commonly used forest growth and yield models. The models were evaluated using landscape scale inventory data from the USDA Forest Service Forest Inventory and Analysis (FIA) Program. To avoid intensively managed forests, only plots of the oak/hickory forest type falling in the Cumberland Plateau region of Alabama, Georgia, and Tennessee were used. A forest scale continuous forest inventory (CFI) data set from the Cumberland Mountains of east Tennessee was also used. The FIA data allowed evaluation of control charts at a large spatial scale while the CFI data were at a smaller spatial scale covering forest stands. Similarly, the re-measurement period of the FIA data were 4-8 years while the re-measurement periods for the CFI data were 5-32 years allowing for evaluation of the utility of control charts at different temporal scales.

Control charts were used to examine trends in growth and yield model accuracy over time. Control charts were also be created for subsets of the data to examine the effects of site and stand conditions on dynamic model accuracy. The subsets were created by partitioning the growth predictions based on variables including site index, stand age, aspect, and slope percent. The control charts will examine model accuracy at multiple points in time.

Data
Two data sets were used in this study. The first was similar to a typical timber inventory collected as part of a continuous forest inventory (CFI) and the second forest inventory was a selected part of the U.S. Forest Service Forest Inventory and Analysis (FIA) program for Tennessee, Georgia, and Alabama. The CFI data consisted of 532 permanent sample plots at four University of Tennessee forest research locations that covered 17,000 acres of forest land across
the state of Tennessee. The data used in this study were a subset of the CFI data from three University of Tennessee owned forest tracts in the Cumberland Mountains of East Tennessee.

In 1962 and 1963, the CFI was initiated by the University of Tennessee Agricultural Experiment Station to study factors influencing forest composition and growth rates (Watson 1979). The objectives of their study were to relate soil and site factors to species composition and growth rates and to establish a modern timber inventory system (Watson 1979). Plots were to be measured every five years, but were only measured four times, with the last re-measurement being in 1977-1978.

The tracts used were part of the University of Tennessee Cumberland Forest Research Station and were referred to as Wilson Mountain, Brushy Mountain, and the Scott County tract. The Wilson and Brushy Mountain tracts were separated by less than a mile. The Scott County, tract was approximately 12 miles north of the Wilson and Brushy Mountain tracts. The plots for Wilson Mountain were established on a regular grid, with 10 chains between plots east to west and 20 chains between plots north to south (Figure 3). The Brushy Mountain Plots were established on a 10 by 16 chain grid with different starting points used in different management compartments (Figure 4). The Scott County plots were spaced 20 chains by 20 chains (Figure 5). To extend the time scale of the CFI data, a subset of 48 plots on the tracts were located and re-measured in 2009. The final result was that Brushy Mountain had 26 plots, Wilson Mountain had 12 plots, and the Scott County tract had 10 plots. Since this study was concerned with accounting for dynamic accuracy, only these 48 plots were of interest across all re-measurements. Average site index and stand age were only recorded during the first measurement in 1962. On each plot, a dominant tree was bored to determine age and the site index for the plot was calculated for that
tree. The original site index for a plot was considered constant over all years used in this study, while stand age for each plot was incremented by the number of years between re-measurements (Table 1).
Figure 3. Wilson Mountain Tract, with plot locations inferred from hand drawn locations on maps created during plot establishment and locations of plots re-measured in 2009 determined by GPS (Cumberland Forest Field Station)
Figure 4. Brushy Mountain Tract, with plot locations inferred from hand drawn locations on maps created during plot establishment and locations of plots re-measured in 2009 determined by GPS (Cumberland Forest Field Station).
Figure 5. Scott County Tract, with plot locations inferred from hand drawn locations on maps created during plot establishment and locations of plots re-measured in 2009 determined by GPS (Cumberland Forest Field Station).
Table 1. Summary of average plot conditions for the three tracts in the Cumberland CFI (BA: basal area ft²/ac, Age: years, SI: site index ft). Standard deviation of Age was 20.288 and SI was 18.673 and remained the same for each year since the values were used for each measurement period. Standard deviation for all the tracts are in parenthesis.

<table>
<thead>
<tr>
<th>Measurement Year</th>
<th>BA</th>
<th>Age</th>
<th>SI</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Brushy (n=26)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1962</td>
<td>49</td>
<td>70</td>
<td>79</td>
</tr>
<tr>
<td>1967</td>
<td>53</td>
<td>75</td>
<td>79</td>
</tr>
<tr>
<td>1972</td>
<td>57</td>
<td>80</td>
<td>79</td>
</tr>
<tr>
<td>1977</td>
<td>65</td>
<td>85</td>
<td>79</td>
</tr>
<tr>
<td>2009</td>
<td>116</td>
<td>117</td>
<td>79</td>
</tr>
<tr>
<td><strong>Wilson(n=12)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1962</td>
<td>73</td>
<td>79</td>
<td>75</td>
</tr>
<tr>
<td>1967</td>
<td>81</td>
<td>84</td>
<td>75</td>
</tr>
<tr>
<td>1972</td>
<td>89</td>
<td>89</td>
<td>75</td>
</tr>
<tr>
<td>1977</td>
<td>76</td>
<td>94</td>
<td>75</td>
</tr>
<tr>
<td>2009</td>
<td>151</td>
<td>126</td>
<td>75</td>
</tr>
<tr>
<td><strong>Scott(n=10)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1962</td>
<td>50</td>
<td>49</td>
<td>80</td>
</tr>
<tr>
<td>1967</td>
<td>58</td>
<td>54</td>
<td>80</td>
</tr>
<tr>
<td>1972</td>
<td>67</td>
<td>59</td>
<td>80</td>
</tr>
<tr>
<td>1977</td>
<td>96</td>
<td>64</td>
<td>80</td>
</tr>
<tr>
<td>2009</td>
<td>130</td>
<td>96</td>
<td>80</td>
</tr>
<tr>
<td><strong>All(n=48)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1962</td>
<td>55 (26.3)</td>
<td>67</td>
<td>78</td>
</tr>
<tr>
<td>1967</td>
<td>61 (28.0)</td>
<td>72</td>
<td>78</td>
</tr>
<tr>
<td>1972</td>
<td>67 (29.2)</td>
<td>77</td>
<td>78</td>
</tr>
<tr>
<td>1977</td>
<td>75 (28.7)</td>
<td>82</td>
<td>78</td>
</tr>
<tr>
<td>2009</td>
<td>128 (33.1)</td>
<td>114</td>
<td>78</td>
</tr>
</tbody>
</table>
Each plot center corresponded to two nested plots, 1/5th acre for sawtimber, and 1/10th acre for pulpwood. Sawtimber trees had a diameter limit of greater than or equal to 10 inches and pulpwood diameter limits were less than 10 inches and greater than 5 inches. A number of measurements were made on each plot, but only tree diameter at breast height (dbh: measured at 4.5 feet above the ground), merchantable and total tree height, tree species, mortality, and in-growth were of interest for this study. All measurements were made on each tree greater than 5 inches in dbh. During the 2009 re-measurement the azimuth to each tree sighted from plot center, the distance from each tree to plot center, and the UTM coordinates of plot center were also recorded. The tools used during re-measurement included: a Laser Technology Impulse rangefinder for tree height, a Haglof Vertex for plot radius and distance from plot center to in-trees, a Spencer Logger’s Tape for tree diameter, a Silva Ranger hand held compass for azimuth from plot center to each in-tree, and a GPS enabled Trimble Nomad field computer for plot center coordinates. The tools used in the measurements from 1962-1977 were a diameter tape, clinometer, topographic and aerial maps, and a handheld compass. Tree heights and distances from trees to plot center were measured in feet to the nearest foot. Tree dbh was measured to the nearest 1/10th of an inch.

The number of plots measured in 2009 for each tract varied by tract size and the ability to locate plots. If a plot could not be located, the nearest plot in the east or west direction was used as the first alternative. If a plot was located, and the plot center stake was not found, marked witness trees whose distance from plot center was recorded in previous inventories were used to relocate plot center. Each plot had two witness trees which were marked with an orange painted ‘X’ and a metal tree tag. All plot centers were re-marked with numbered 18-24 inch long pieces of PVC
pipe in 2009. In the previous inventories in-trees were marked with metal tags etched with a tree id number and nailed to the tree above breast height. No new tags were installed in 2009 because azimuth and distance were recorded for each tree on the nested plots.

The FIA data that were used were from Tennessee, Alabama, and Georgia and were obtained from the U.S. Forest Service’s data mart website at http://199.128.173.17/fiadb4-downloads/datamart.html on August 17, 2010. This study was limited to plots the U.S. Forest Service defined as the oak/hickory group. This group was selected because tree species found on the University of Tennessee forest tracts consist of the same species. The forest types with-in the oak/hickory group included chestnut oak, white oak/red oak/hickory, white oak, northern red oak, yellow poplar/white oak/northern red oak, sweetgum/yellow poplar, scarlet oak, yellow poplar, chestnut oak/black oak/scarlet oak, red maple/oak, and mixed upland hardwoods (USFS 2005). The states selected were Alabama, Georgia, and Tennessee. These states were selected because sections of the states were in the Cumberland Plateau region. Although Kentucky was also in the Cumberland Plateau region, the most recent re-measurement data were unavailable so it was excluded from this study. The two most recent measurements were used with the first measurement period including plots installed from 1998-2004. The plots were then re-measured between 2005 and 2008. Plots that had any major disturbances, high mortality, or evidence of harvest were not used because species composition of the plots may have changed and the dynamic model accuracy of models under these circumstances was not of interest. Across the 5 periodic measurements a total of 728 plots in the oak/hickory forest type that were re-measured in the 3 target states and these plots will be used in this study (Figure 6).
Figure 6. Fuzzed FIA plot locations for plots used in this study. The FIA uses fuzzed latitude and longitude that were within 1mi of the actual plot location to protect landowner privacy (http://199.128.173.17/fiadb4-downloads/datamart.html).
The FIA plot design consisted of four subplots for each plot location with the first subplot located in the middle and the other three subplots centers extending out 120 ft at azimuths of 0°, 120°, and 240° from the first subplot center. Each subplot was circular with a 24 ft radius (USFS 2005). The data for each measurement cycle included separate tables for plot-level, county-level, tree-level, and subplot-level measurements. Tables were linked and summarized as needed using Microsoft Access to generate the input data for the growth and yield models and subsequent control charts. Microsoft Access was used to combine relevant data from the different tables into a single table for each measurement year. Each year’s table included columns for plot number, county, measurement cycle, tree number, dbh, height, site index, stand age, forest type and basal area per acre for each plot. Site index was a key input variable for the growth and yield models and was already calculated in the FIA data tables. The average growth period length between plot re-measurement was 5.5 years (Table 2).
Table 2. Summary of average plot growth and yield model input variables from the FIA data with standard deviations in parenthesis.

<table>
<thead>
<tr>
<th>Measurement Year</th>
<th>Basal Area (ft$^2$/ac)</th>
<th>SI (ft) Base Age 50</th>
<th>Stand Age (Yrs)</th>
<th>Number Plots</th>
<th>Growth Period Length (Yrs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1998</td>
<td>62 (33.6)</td>
<td>75 (14.5)</td>
<td>49 (16.8)</td>
<td>18</td>
<td>8.1</td>
</tr>
<tr>
<td>1999</td>
<td>85 (31.6)</td>
<td>83 (16.7)</td>
<td>53 (18.3)</td>
<td>62</td>
<td>7</td>
</tr>
<tr>
<td>2000</td>
<td>90 (30.5)</td>
<td>81 (15.1)</td>
<td>58 (16.5)</td>
<td>155</td>
<td>5.3</td>
</tr>
<tr>
<td>2001</td>
<td>86 (36.6)</td>
<td>78 (17.1)</td>
<td>57 (19.8)</td>
<td>174</td>
<td>5.1</td>
</tr>
<tr>
<td>2002</td>
<td>86 (33.5)</td>
<td>82 (16.8)</td>
<td>55 (19.4)</td>
<td>184</td>
<td>4.8</td>
</tr>
<tr>
<td>2003</td>
<td>82 (30.2)</td>
<td>77 (15.1)</td>
<td>56 (21.0)</td>
<td>128</td>
<td>4.3</td>
</tr>
<tr>
<td>2004</td>
<td>64 (22.2)</td>
<td>84 (20.1)</td>
<td>57 (37.8)</td>
<td>7</td>
<td>4</td>
</tr>
</tbody>
</table>
Methods

Implementation of WinYield
The input variables for WinYield were individual plot basal area, stand age, and site index. Plot growth predictions were made for the FIA plots and the CFI plots. The WinYield calculations were done in Microsoft Excel using the upland oak formula employed in WinYield (Equation [1], (Dale 1972).

\[ Y = -B \times A^{-0.08} \times \ln B + 3.68521 \times B \times A^{-0.75} + 0.011383 \times B \times S \times A^{-1.05} \]  

[1]

Where:
B is basal area of the plot (ft²/ac);
A is stand age of the plot in years;
S is site index of the plot in (ft) at base age 50 for dominant tree on plot in 1962;
Y is the net annual basal area growth for all trees greater than 5.0 inches.

Implementation of FVS
The SUPPOSE graphical user interface for FVS was used to input data, output data, and manage plot level growth and yield projections across the various prediction periods (downloaded from the U.S. Forest Service website at http://www.fs.fed.us/fmsc/fvs/software/suppose.php on May 19th, 2010). The Southern Variant of FVS was down loaded on May 19th, 2010 at http://www.fs.fed.us/fmsc/fvs/variants/sn.php. To get the data into SUPPOSE, the Forest Service uses a database extension that provided a downloadable template in Microsoft Access and included two tables: StandInit and TreeInit (Shaw 2009). The StandInit table required: plot number, stand id (same as plot number in this case), FVS variant, stand age, plot expansion factor, number of subplots for each plot, stocking percent of subplots that were forested, site index, forest type, state ID, and county ID. The plot expansion factor was 24 for each subplot because the plots were composed of four 1/24th acre subplots. The stocking percent was the
number of subplots classified as forested plots divided by four, the total number of subplots. If all the plots were non-forestland, the plot was dropped from the data set. The TreeInit table included the variables: plot number, stand id, tree species, diameter (inches), height (feet), and stand age (years). The output from FVS was digitally inserted into the originating Microsoft Access database. The output basal area and year were used in creating the control charts.

**Formulation of control charts**

Once growth predictions (with either FVS or WinYield) were made for all selected plots (either FIA or CFI), control charts were formed. The following steps were used to create all control charts.

1. Determine the basal area of each plot at the current measurement year \( (t_i) \) and the next measurement year \( (t_{i+1}) \).

2. Calculate the annual change in measured basal per acre across the growth period between \( t_i \) and \( t_{i+1} \) for each plot \( j \).

\[
\Delta BA_{(i+1)j} = \frac{BA_{(i+1)j} - BA_{ij}}{t_{i+1} - t_i}
\]

Where:

\( \Delta BA_{(i+1)j} \) was change in basal area of the \( j \)th plot for the time \( t_i \) to \( t_{i+1} \);

\( BA_{ij} \) was basal area of the \( j \)th plot at the \( i \)th measurement year;

\( t_i \) was the \( i \)th measurement year;

\( t_{i+1} \) was the next measurement year.

3. For each measurement year take the standard deviation \( (\sigma) \) of \( \Delta BA_{(i+1)j} \) (Equation [2])
\[ \sigma_{i+1} = \sqrt{\frac{\sum_{j=1}^{n}(\Delta BA_{(i+1)j} - \overline{\Delta BA_{(i+1)}})^2}{n - 1}} \]  \[ \text{[3]} \]

Where:

\( \sigma_{i+1} \) was standard deviation of basal area change from time \( t_i \) to \( t_{i+1} \) across the included plots;

\( \Delta BA_{(i+1)j} \) was change in basal area of the \( j^{th} \) plot from time \( t_i \) to \( t_{i+1} \);

\( \overline{\Delta BA_{(i+1)}} \) was the mean basal area change from time \( t_i \) to \( t_{i+1} \) across the included plots;

\( n \) was number of included plots.

4. Calculate confidence limits for each measurement year as

\[ LCL_{i+1} = \frac{-c \sigma_i}{\sqrt{n_i}} \]  \[ \text{[4]} \]

\[ UCL_{i+1} = \frac{c \sigma_i}{\sqrt{n_i}} \]

Where:

LCL was the lower confidence limit at time \( i \);

UCL was the upper confidence limit at time \( i \);

c was a constant set to 2 or 3 standard deviations away from the mean;

\( n \) was the number of plots measured at time \( i \).

5. Calculate the annual difference between predicted and measured basal area change for each plot as

\[ \Delta BA_{\text{diff}}_{ij} = \left( \frac{\Delta BA_{(i+1)j} - \Delta BAP_{(i+1)j}}{t_{i+1} - t_i} \right) = \left( \frac{BA_{(i+1)j} - BAP_{(i+1)j}}{t_{i+1} - t_i} \right) \]  \[ \text{[5]} \]
Where:

\[ \Delta BA_{diff}(i+1)_j \] was the annualized difference between predicted and measured growth for plot \( j \) from time \( t_i \) to \( t_{i+1} \);
\[ \Delta BA_{ij} \] was from Equation [2];
\[ \Delta BAP_{ij} \] was the model predicted basal area change of the \( j \)th plot for time \( t_i \) to \( t_{i+1} \);
\[ BA_{(i+1)j} \] was the measured basal area of plot \( j \) at the time \( i + 1 \);
\[ BAP_{(i+1)j} \] was the model predicted basal area of plot \( j \) at time \( i + 1 \);
\( t_i \) was \( i \)th measurement year;
\( t_{i+1} \) was the next measurement year.

6. Calculate the error as the mean difference between the annualized predicted and measured growth.

\[
\overline{\Delta BA_{diff}}_{i+1} = \frac{\sum_{j=1}^{n} \Delta BA_{diff}(i+1)_j}{n_i}
\]

[6]

Where:

\( \overline{\Delta BA_{diff}}_{i+1} \) was the mean difference at re-measurement;
\( \Delta BA_{diff}(i+1)_j \) was the difference between predicted and measured growth for plot \( j \) at re-measurement \( i+1 \) (Equation [5]);
\( n_i \) was the number of plots measured at time \( i \).

7. The y-axis of the control chart was the average difference in annual basal area growth per acre (ft\(^2\)/ac/yr) and the x-axis was the prediction year. The LCL and UCL from Equation [4] and the \( \overline{\Delta BA_{diff}}_{i+1} \) were plotted against the y-axis.
8. Repeat for each re-measurement year $i$.

The $c$ values in Equation [3] were set at both 2 and 3 comparable to 95% and 99% confidence intervals, respectively. The constant of three was commonly used in statistical control because it helps ensure process stability, while two sigma helps detect smaller shifts in the process (Chandra 2001). If the mean error between predicted and measured mean annual basal area growth went above the UCL or below the LCL, the process was considered to be out of control at that time. An out of control process indicated that the model failed to give accurate predictions for that re-measurement year. A small selection of plots from one re-measurement time period for the CFI data projected using FVS were used to create an example of control chart formulation (Table 3 and Table 4). To create the final control chart all plots were used and the steps were repeated for three additional prediction periods.
Table 3. Example of data and calculations needed to create control charts. Data are from 8 example CFI plots and predictions were made using WinYield.

<table>
<thead>
<tr>
<th>Plot Number</th>
<th>Site Index (ft)</th>
<th>Age (Yr)</th>
<th>(BA_{(i)}) (ft(^2)/ac)</th>
<th>(BA_{(i+1)}) (ft(^2)/ac)</th>
<th>(BAP_{(i+1)}) (ft(^2)/ac)</th>
<th>(\Delta BA_{(i+1)}) (ft(^2)/ac)</th>
<th>(BA_{(i+1)} - BAP_{(i+1)}) (ft(^2)/ac)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>65</td>
<td>60</td>
<td>53</td>
<td>61</td>
<td>31</td>
<td>-39</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>94</td>
<td>79</td>
<td>45</td>
<td>50</td>
<td>53</td>
<td>-5</td>
<td>-3</td>
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<tr>
<td>3</td>
<td>106</td>
<td>64</td>
<td>56</td>
<td>69</td>
<td>68</td>
<td>-13</td>
<td>1</td>
</tr>
<tr>
<td>4</td>
<td>90</td>
<td>56</td>
<td>37</td>
<td>40</td>
<td>45</td>
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<td>-5</td>
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<td>5</td>
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<td>76</td>
<td>34</td>
<td>51</td>
<td>41</td>
<td>-17</td>
<td>10</td>
</tr>
<tr>
<td>6</td>
<td>64</td>
<td>95</td>
<td>26</td>
<td>27</td>
<td>30</td>
<td>-1</td>
<td>-3</td>
</tr>
<tr>
<td>7</td>
<td>64</td>
<td>74</td>
<td>35</td>
<td>39</td>
<td>42</td>
<td>-4</td>
<td>-3</td>
</tr>
<tr>
<td>8</td>
<td>65</td>
<td>74</td>
<td>44</td>
<td>44</td>
<td>51</td>
<td>0</td>
<td>-7</td>
</tr>
</tbody>
</table>
Table 4. Example summary of the data from Table 3 (ft$^2$/ac/yr) needed to plot one year of data in a control chart.

<table>
<thead>
<tr>
<th>Year</th>
<th>$\Delta BA_{(i+1)}$</th>
<th>Years</th>
<th>$\sigma_{i+1}$</th>
<th>n</th>
<th>$\Delta BA_{diff_{i+1}}$</th>
<th>$UCL_{i+1}$ (3σ)</th>
<th>$LCL_{i+1}$ (3σ)</th>
<th>$UCL_{i+1}$ (2σ)</th>
<th>$LCL_{i+1}$ (2σ)</th>
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</thead>
<tbody>
<tr>
<td>1962</td>
<td>14.402</td>
<td>5</td>
<td>2.880</td>
<td>8</td>
<td>-1.225</td>
<td>3.055</td>
<td>-3.055</td>
<td>2.037</td>
<td>-2.037</td>
</tr>
<tr>
<td>1967</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Results
The Forest Vegetation Simulator and WinYield were used to predict annual basal area growth for both the Cumberland CFI data and the regional FIA data. Table 5 and Table 6 include the difference between measured and predicted annual basal area growth for the FIA and CFI data sets, with negative differences representing a predicted growth that was greater than measured growth and positive differences representing measured growth that was greater than predicted growth. The WinYield growth equation gave more accurate growth predictions for both the CFI and FIA data sets.
Table 5. Summary of re-measured and predicted basal area for the FIA data using both the WinYield and FVS growth models. The differences are between predicted and actual BA for the indicated year. All values were averaged across the 728 FIA plots and are in (ft$^2$/ac).

<table>
<thead>
<tr>
<th>Year</th>
<th>$\overline{BA}$</th>
<th>WinYield $\overline{BAP}$</th>
<th>FVS $\overline{BAP}_{(i+1)}$</th>
<th>WinYield $\overline{BA}<em>{(i+1)} - \overline{BAP}</em>{(i+1)}$</th>
<th>FVS $\overline{BA}<em>{(i+1)} - \overline{BAP}</em>{(i+1)}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>2005</td>
<td>96.265</td>
<td>96.163</td>
<td>98.685</td>
<td>-0.102</td>
<td>2.421</td>
</tr>
<tr>
<td>(n=170)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2006</td>
<td>93.689</td>
<td>94.119</td>
<td>95.546</td>
<td>0.430</td>
<td>1.857</td>
</tr>
<tr>
<td>(n=229)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2007</td>
<td>96.025</td>
<td>95.572</td>
<td>97.563</td>
<td>-0.453</td>
<td>1.538</td>
</tr>
<tr>
<td>(n=252)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2008</td>
<td>86.418</td>
<td>87.096</td>
<td>88.125</td>
<td>0.678</td>
<td>1.707</td>
</tr>
<tr>
<td>(n=77)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 6. Summary of re-measured and predicted basal area for the CFI data using both the WinYield and FVS growth models. The differences are between average predicted and average measured BA for the indicated year. All values were averaged across the 48 CFI plots and are in (ft$^2$/ac).

<table>
<thead>
<tr>
<th>Prediction Year</th>
<th>WinYield $BA$</th>
<th>WinYield $BAP_{(i+1)}$</th>
<th>FVS $BA$</th>
<th>FVS $BAP_{(i+1)}$</th>
<th>WinYield $BA_{(i+1)} - BAP_{(i+1)}$</th>
<th>FVS $BA_{(i+1)} - BAP_{(i+1)}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1967</td>
<td>60.875</td>
<td>62.726</td>
<td>65.396</td>
<td>-1.851</td>
<td>-4.521</td>
<td></td>
</tr>
<tr>
<td>1972</td>
<td>66.750</td>
<td>67.640</td>
<td>70.917</td>
<td>-0.890</td>
<td>-4.167</td>
<td></td>
</tr>
<tr>
<td>1977</td>
<td>75.146</td>
<td>72.746</td>
<td>77.250</td>
<td>2.400</td>
<td>-2.104</td>
<td></td>
</tr>
<tr>
<td>2009</td>
<td>127.896</td>
<td>103.920</td>
<td>156.625</td>
<td>23.975</td>
<td>-28.729</td>
<td></td>
</tr>
</tbody>
</table>
Control Charts
Control charts indicated when the process of using growth and yield models went out of control and become inaccurate. If the difference between measured and predicted mean basal area growth per acre per year (Equation [6]) was close to zero and between the upper and lower confidence limits (Equation [4]), the growth model was considered in control and accurate for that time period. If the difference fell outside the confidence limits, the growth model is considered inaccurate for that growth period. In all control charts, the FVS results were represented with a plus sign (⁺) and the WinYield results were represented with a diamond (◊).

The upper and lower confidence intervals for 3σ are dashed lines and 2σ are dotted lines. The confidence limits are the same for both WinYield and FVS in each control chart because the limits are based on the difference between measured plot basal area at $t_i$ and re-measured plot basal area at $t_{i+1}$.

When predicting growth for the CFI plots, the WinYield predictions were within the confidence limits for all the 5 year predictions, but the 32 year 2009 prediction was out of control, predicting lower basal area growth per year than was observed (Figure 7). There also appeared to be a trend with prediction accuracy for each successive growth period getting closer to out of control. The FVS results were out of control at 2σ for the first prediction year (1967) and out of control at 3σ for the 2009 prediction (Figure 7). The 32 year prediction was out of control here because FVS predicted lower annual basal area growth than measured growth.

For the regional, shorter term FIA data, the WinYield results were all within the confidence limits and were all close to having no difference between measured and predicted growth (Figure 8). The FVS results were out of control for the 2σ control limit at the 2005 and 2006 prediction
years (Figure 8). For FVS the control chart indicated that the difference between actual and predicted growth was getting smaller for more recent re-measurements.
Figure 7. Control chart indicating difference between predicted and measured annual basal area growth from the CFI data with predictions made with both WinYield and FVS, and confidence limits as indicated for each prediction year in which a re-measurement occurred. Values were calculated across all 48 plots.
Figure 8. Control chart indicating difference between predicted and measured annual basal area growth from the FIA data with predictions made with both WinYield and FVS, and confidence limits as indicated for each prediction year in which a re-measurement occurred. Values were calculated across all 728 plots (Table 5).
Control charts for subset of stand age
The errors seen for the older stands in the CFI data at the end of the long growth period suggest that there may be interactions between model accuracy and stand age. To attempt to separate these interactions from interactions between model accuracy and environmental change, control charts were created for plots that were subset by stand age. Plots were subset for both the CFI and FIA data. The CFI data set was divided into plots that had a stand age younger than 67 in 1962 and older than 67 in 1962. The age of 67 was chosen because it was the mean age of trees on the plots measured in 1962. The plots were assigned to each subgroup for all prediction periods.

For younger CFI plots (< 67 years), the WinYield growth prediction was out of control for the 1977 prediction at the 2σ control limit and for the 2009 prediction at the 3σ limit (Figure 9). The WinYield equation resulted increasing under prediction of growth for each successive re-measurement. The FVS predictions were out of control for the 1967 prediction at the 2σ limit and for the 2009 prediction at the 3σ limit (Figure 9). The FVS chart indicated a decrease in over prediction over each time period for the first three prediction years, while the 2009 prediction was over predicted and outside the lower 3σ control limit. For older plots (> 67 years), there was no consistent trend in prediction accuracy for WinYield or FVS (Figure 10). The 1972 and 2009 predictions were out of control for WinYield and the 2009 prediction was out of control using FVS. Also, the 5 year predictions were all around the 2σ limits for the FVS results.

To examine age effects in the FIA data that data set was divided into thirds, with the first third being the youngest stands and the last third being the oldest stands at each re-measurement period (Table 7). Average measurement year stand age was used at each re-measurement period.
because it was an input to the FVS model. For the youngest plots (15-48 years), the growth predictions were in control (Figure 11). For the middle aged plots (44-66 years), the growth predictions for both models were in control (Figure 12). For the oldest plots (63-120 years), the control chart indicated growth being out of control for the 2007 prediction using WinYield at the 2σ control limit and out of control for the 2006 and 2008 predictions using FVS at the 2σ control limit (Figure 13). The youngest 1/3 and middle 1/3 stand ages were within the 2σ control limits, unlike when using all plots, where the FIA data were out of control at the 2σ limit.
Table 7. Breakdown of stand ages for each re-measurement period for the FIA data.

<table>
<thead>
<tr>
<th>Year</th>
<th>Youngest 1/3</th>
<th>Middle 1/3</th>
<th>Oldest 1/3</th>
<th>Number Plots/Yr</th>
</tr>
</thead>
<tbody>
<tr>
<td>2005</td>
<td>15-48 (n=57)</td>
<td>48-66 (n=57)</td>
<td>67-113 (n=56)</td>
<td>170</td>
</tr>
<tr>
<td>2006</td>
<td>15-47 (n=76)</td>
<td>47-64 (n=76)</td>
<td>65-120 (n=77)</td>
<td>229</td>
</tr>
<tr>
<td>2007</td>
<td>16-45 (n=84)</td>
<td>46-62 (n=84)</td>
<td>63-118 (n=84)</td>
<td>252</td>
</tr>
<tr>
<td>2008</td>
<td>18-44 (n=26)</td>
<td>44-66 (n=26)</td>
<td>66-120 (n=25)</td>
<td>77</td>
</tr>
<tr>
<td></td>
<td>Plots</td>
<td></td>
<td></td>
<td>243</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>243</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>242</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>728</td>
</tr>
</tbody>
</table>
Table 8. Breakdown of stand ages and plots for each re-measurement period for the CFI data.

<table>
<thead>
<tr>
<th>Re-Measurement</th>
<th>Plots</th>
<th>Re-Measurement</th>
<th>Plots</th>
</tr>
</thead>
<tbody>
<tr>
<td>1967</td>
<td>24</td>
<td>1967</td>
<td>24</td>
</tr>
<tr>
<td>1972</td>
<td>24</td>
<td>1972</td>
<td>24</td>
</tr>
<tr>
<td>1977</td>
<td>24</td>
<td>1977</td>
<td>24</td>
</tr>
<tr>
<td>2009</td>
<td>24</td>
<td><strong>2009</strong></td>
<td><strong>24</strong></td>
</tr>
</tbody>
</table>
Figure 9. Control chart indicating difference between predicted and measured annual basal area growth from the CFI data with predictions made with both WinYield and FVS, and confidence limits as indicated for each prediction year in which a re-measurement occurred. Values were calculated across stand ages less than 67 years old. See Table 8 for number of plots at each re-measurement.
Figure 10. Control chart indicating difference between predicted and measured annual basal area growth from the CFI data with predictions made with both WinYield and FVS, and confidence limits as indicated for each prediction year in which a re-measurement occurred. Values were calculated across stand ages greater than 67 years old. See Table 8 for number of plots at each re-measurement.
Figure 11. Control chart indicating difference between predicted and measured annual basal area growth from the FIA data with predictions made with both WinYield and FVS, and confidence limits as indicated for each prediction year in which a re-measurement occurred. Values were calculated across plots with the youngest 1/3 of stand ages for each prediction period. See Table 7 for number of plots at each re-measurement.
Figure 12. Control chart indicating difference between predicted and measured annual basal area growth from the FIA data with predictions made with both WinYield and FVS, and confidence limits as indicated for each prediction year in which a re-measurement occurred. Values were calculated across plots with the middle 1/3 of stand ages for each prediction period. See Table 7 for number of plots at each re-measurement.
Figure 13. Control chart indicating difference between predicted and measured annual basal area growth from the FIA data with predictions made with both WinYield and FVS, and confidence limits as indicated for each prediction year in which a re-measurement occurred. Values were calculated across plots with the oldest 1/3 of stand ages for each prediction period. See Table 7 for number of plots at each re-measurement.
Control charts limiting site index
Site index was subset with the expectation that lower quality forest sites would result in slower growth while higher quality sites would result in faster growth. This may have an effect on response to environmental change. Both FVS and WinYield models used site index as an indicator of site quality. Plots were subset by site index for both data sets. The CFI data were limited to above and below a mean site index of 76. The CFI site index was calculated from the 1962 bored tree age and from that tree species site index curve assumption at base age 50. The FIA data were divided into thirds going from the lowest site index to the highest at each re-measurement (Table 9).

Control charts for the poor site quality (site index < 76 ft) CFI plots indicated that WinYield increased under prediction over time after 1972, while FVS over predicted at all times (Figure 14). All of the FVS predictions were in control with the 1977 and 2009 predictions closest to no difference between measured and predicted growth. For the high site quality (site index >= 76) CFI plots the 2009 prediction using FVS is out of control for poor site quality sites while it was in control for high quality sites (Figure 15). The 2009 WinYield prediction was within the 3σ limit for high quality sites, but beyond the 2σ limit for poor quality sites. The control charts for the FVS model resulted in more accurate growth predictions for lower quality sites while the control charts for the WinYield model resulted in more accurate growth predictions for higher quality sites.

For the high, medium, and low site index plots of the FIA data, the control charts indicated that all prediction periods were in control (Figure 16, Figure 17, and Figure 18). The predictions followed similar trends over all the periods. The highest third of site index plots had most
accurate predictions among all the previous control charts (Figure 18). The WinYield and FVS predictions were similar to each other for every year. Limiting site index had no effect on the accuracy of the relatively short range predictions associated with the FIA data.
Table 9. Breakdown of site index for each re-measurement period for the FIA data.

<table>
<thead>
<tr>
<th>Year</th>
<th>Lowest 1/3</th>
<th>Middle 1/3</th>
<th>Highest 1/3</th>
<th>Number Plots/Yr</th>
</tr>
</thead>
<tbody>
<tr>
<td>2005</td>
<td>47-73 (n=57)</td>
<td>73-87 (n=57)</td>
<td>87-122 (n=56)</td>
<td>170</td>
</tr>
<tr>
<td>2006</td>
<td>46-71 (n=76)</td>
<td>71-86 (n=76)</td>
<td>87-132 (n=77)</td>
<td>229</td>
</tr>
<tr>
<td>2007</td>
<td>48-71 (n=84)</td>
<td>71-84 (n=84)</td>
<td>84-129 (n=84)</td>
<td>252</td>
</tr>
<tr>
<td>2008</td>
<td>47-71 (n=26)</td>
<td>72-84 (n=26)</td>
<td>84-118 (n=25)</td>
<td>77</td>
</tr>
<tr>
<td></td>
<td>Plots</td>
<td>243</td>
<td>243</td>
<td>242</td>
</tr>
</tbody>
</table>
Table 10. Breakdown of site index for each re-measurement period for the CFI data.

<table>
<thead>
<tr>
<th>Re-Measurement</th>
<th>Plot 1</th>
<th>Re-Measurement</th>
<th>Plot 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1967</td>
<td>24</td>
<td>1967</td>
<td>24</td>
</tr>
<tr>
<td>1972</td>
<td>24</td>
<td>1972</td>
<td>24</td>
</tr>
<tr>
<td>1977</td>
<td>24</td>
<td>1977</td>
<td>24</td>
</tr>
<tr>
<td>2009</td>
<td>24</td>
<td>2009</td>
<td>24</td>
</tr>
</tbody>
</table>
Figure 14. Control chart indicating difference between predicted and measured annual basal area growth from the CFI data with predictions made with both WinYield and FVS, and confidence limits as indicated for each prediction year in which a re-measurement occurred. Values were calculated across plots with site index values less than 76ft. See Table 10 for number of plots at each re-measurement period.
Figure 15. Control chart indicating difference between predicted and measured annual basal area growth from the CFI data with predictions made with both WinYield and FVS, and confidence limits as indicated for each prediction year in which a re-measurement occurred. Values were calculated across plots with site index values greater than 76ft. See Table 10 for number of plots at each re-measurement period.
Figure 16. Control chart indicating difference between predicted and measured annual basal area growth from the FIA data with predictions made with both WinYield and FVS, and confidence limits as indicated for each prediction year in which a re-measurement occurred. Values were calculated across plots with the lowest 1/3 site index values for each prediction period. See Table 9 for number of plots at each re-measurement.
Figure 17. Control chart indicating difference between predicted and measured annual basal area growth from the FIA data with predictions made with both WinYield and FVS, and confidence limits as indicated for each prediction year in which a re-measurement occurred. Values were calculated across plots with the middle 1/3 site index values for each prediction period. See Table 9 for number of plots at each re-measurement.
Figure 18. Control chart indicating difference between predicted and measured annual basal area growth from the FIA data with predictions made with both WinYield and FVS, and confidence limits as indicated for each prediction year in which a re-measurement occurred. Averages are across plots with the highest \( \frac{1}{3} \) site index values for each prediction period. See Table 9 for number of plots at each re-measurement.
Control charts using stand stocking percent
To further evaluate control charts, the FIA plot data were divided into stocking percents classified by FIA standards and were in three categories were used: fully stocked (60-99%), moderately stocked (35-59%), and poorly stocked (10-34%) (USFS 2005). FIA stand stocking percent here was not the same as the stocking percent of subplots that was an input in FVS. The input stocking percent in FVS was the percent of subplots that were forested. Stocking percent here was a measure of density of trees per acre or basal area per acre. The stocking percent subsets were created to determine if control charts indicated any trends in accuracy of forest growth predictions due to differences in levels of competition indicated by stocking percent. The CFI data was not divided into stocking percent because of the relatively few number of plots. Control charts indicated that the WinYield predictions for fully stocked plots were out of control for the 2006 and 2007 years (Figure 19). Control charts indicated that the FVS predictions for fully stocked stands were all within the confidence limits. For the moderately stocked plots, the trends in the control charts for WinYield and FVS were similar with the only difference that all the WinYield predictions were within the 2σ control limit (Figure 20). Figure 21 represents poorly stocked plots and each successive prediction year was closer to being out of control with the 2008 prediction period being out of control for both WinYield and FVS. Control charts limiting stocking percent determined that moderately stocked stands were most accurately projected.
Table 11. Breakdown of the number of plots by FIA stocking percent.

<table>
<thead>
<tr>
<th>Year</th>
<th>Fully Stocked (60-99%)</th>
<th>Moderately Stocked (35-59%)</th>
<th>Poorly Stocked (10-34%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2005</td>
<td>59</td>
<td>86</td>
<td>29</td>
</tr>
<tr>
<td>2006</td>
<td>60</td>
<td>126</td>
<td>46</td>
</tr>
<tr>
<td>2007</td>
<td>72</td>
<td>136</td>
<td>46</td>
</tr>
<tr>
<td>2008</td>
<td>20</td>
<td>50</td>
<td>13</td>
</tr>
<tr>
<td>Plots</td>
<td>211</td>
<td>398</td>
<td>134</td>
</tr>
</tbody>
</table>
Figure 19. Control chart indicating difference between predicted and measured annual basal area growth from the FIA data with predictions made with both WinYield and FVS, and confidence limits as indicated for each prediction year in which a re-measurement occurred. Values were calculated across the fully stocked stands for each prediction period. See Table 11 for number of plots for each re-measurement period.
Figure 20. Control chart indicating difference between predicted and measured annual basal area growth from the FIA data with predictions made with both WinYield and FVS, and confidence limits as indicated for each prediction year in which a re-measurement occurred. Values were calculated across the moderately stocked stands for each prediction period. See Table 11 for number of plots for each re-measurement period.
Figure 21. Control chart indicating difference between predicted and measured annual basal area growth from the FIA data with predictions made with both WinYield and FVS, and confidence limits as indicated for each prediction year in which a re-measurement occurred. Values were calculated across the poorly stocked stands for each prediction period. See Table 11 for number of plots for each re-measurement period.
Control charts for slope aspect
Control charts were also formulated for plots with north and south facing slopes respectively, for the FIA data. Aspect was selected because control charts may expose how precipitation changes can affect growth predictions. South facing slopes receive more sunlight, while north facing slopes have been cooler, and moister. In the Appalachian Mountains, Barnes et al. (1998) found northeast slopes were the most productive. The CFI data were not used because slope aspect was not recorded in the inventory and there were only 48 re-measured plots. Each FIA plot had a measured azimuth for slope direction. Plots that were considered north facing had azimuths between 45° and 315° and south facing slopes had azimuths of 135° and 225° (Table 12).

Predictions for plots on south facing slopes were all in control, but from 1998 to 2001 and from 2005 to 2008 the average annual precipitation for Tennessee, Alabama, and Georgia was lower than the average annual precipitation indicating that drought conditions may not effect tree growth predictions (Figure 1). The FVS model over predicted annual basal area growth for all the prediction periods except for 2006 (Figure 23). The WinYield model under predicted basal area growth for the 2006 and 2007 measurements, but it followed the same trend as FVS. The control charts indicated north facing slopes (Figure 23) were more accurately projected, with WinYield and FVS following similar trends and being more accurate, than the south facing slopes (Figure 22).
Table 12. Breakdown of plots for north (Aspect = 45°- 315°) and south (Aspect = 135° and 225°) facing slopes for each re-measurement period for the FIA data.

<table>
<thead>
<tr>
<th>Year</th>
<th>South</th>
<th>North</th>
</tr>
</thead>
<tbody>
<tr>
<td>2005</td>
<td>39</td>
<td>31</td>
</tr>
<tr>
<td>2006</td>
<td>50</td>
<td>33</td>
</tr>
<tr>
<td>2007</td>
<td>52</td>
<td>35</td>
</tr>
<tr>
<td>2008</td>
<td>18</td>
<td>15</td>
</tr>
<tr>
<td>Total</td>
<td>159</td>
<td>114</td>
</tr>
</tbody>
</table>
Figure 22. Control chart indicating difference between predicted and measured annual basal area growth from the FIA data with predictions made with both WinYield and FVS, and confidence limits as indicated for each prediction year in which a re-measurement occurred. Values calculated across the south facing plots for each prediction period. See Table 12 for number of plots for each re-measurement period.
Figure 23. Control chart indicating difference between predicted and measured annual basal area growth from the FIA data with predictions made with both WinYield and FVS, and confidence limits as indicated for each prediction year in which a re-measurement occurred. Values calculated across the north facing plots for each prediction period. See Table 12 for number of plots for each re-measurement period.
Control charts for past CFI pine/hardwood plots
Up to 1977 some CFI plots had pine species mixed with hardwoods. The re-measurement in 2009 had 48 plots and 13 of them previously had significant amounts of pine. Only 1 plot still had pine in 2009 and was excluded from this part of the study. There were a total of 313 trees on the 12 re-measured plots in 1977 and 84 of the trees were classified as pine. The re-measurement plots that previously had pine located on them were divided with plots that had no pine on them in the past. Control charts were used to determine if these differences in species composition affected growth predictions in a way that was detectable with control charts. The species composition of the historic plots that had pine mixed with hardwoods was altered because of the southern pine beetle impact in the mid to late 1970’s and from 1999-2002. The FIA data were not used here because the species composition was constrained during data selection. The plots that had pine previously on them and have no pine currently were accurately projected using both FVS and WinYield (Figure 24). The plots that did not have pine located on them in 1977 resulted in inaccurate long-term growth predictions (Figure 25).
Figure 24. Control chart indicated difference between predicted and measured annual basal area growth from the CFI data with predictions made with both WinYield and FVS, and confidence limits as indicated for each prediction year in which a re-measurement occurred. Values calculated across plots that previously had pine mixed with hardwoods and currently does not have pine for each prediction period (12 plots at each re-measurement year).
Figure 25. Control chart indicating difference between predicted and measured annual basal area growth from the CFI data with predictions made with both WinYield and FVS, and confidence limits as indicated for each prediction year in which a re-measurement occurred. Averages are across plots that previously had no pine mixed with hardwoods and currently does not have pine for each prediction period (35 plots at each re-measurement year).
Discussion
The first control charts evaluated used all of the CFI and FIA plot level data. Those control charts indicated that all of the growth predictions for the short FIA and CFI prediction periods (<8 years) remained in-control within the 3σ limits (Figure 7 and Figure 8). However, the growth during long prediction period (1977-2009) from the CFI re-measurement was inaccurately predicted by both FVS and WinYield. For the long prediction period, FVS over predicted and WinYield under predicted (Figure 7 and Figure 8). This result led to further attempts to identify the cause of this inaccuracy using additional control charts. Subsets of the data were used to create subsequent control charts to evaluate their utility in identifying causes of model inaccuracy.

The first subsets were created based on stand age (Figure 9 to Figure 13). Age specific control charts indicated that younger stands using both WinYield and FVS for the CFI and FIA data sets were more accurate for the 4-8 year growth periods when compared to the long prediction period. Again, this was not the case for the long CFI growth period. As with all the data, the growth prediction remained out of control. Because the control charts for young stands and old stand were in control it is safe to assume that model accuracy was not related to the age of trees.

The next subsets were created to evaluate model accuracy at different site indexes (Figure 14 to Figure 18). Site index specific control charts indicated that all the projections of the CFI growth were accurate. The control charts using WinYield were accurate for higher site index plots (Figure 15), while FVS was accurate for lower site index plots (Figure 14). For the FIA data, control charts indicated accurate growth predictions for all levels of site index used. The control charts diagnosed that site index did affect the accuracy of long-term growth predictions. The
control charts also indicated that FVS and WinYield accuracies were affected differently by variation in site index.

Rauscher and Young (2000) tested the accuracy of growth and yield models for southern hardwood forests using confidence interval estimation. One of the data sets they used consisted of 236 permanent upland hardwood plots and 49 permanent bottomland hardwood plots. Some of the plots were located in Georgia and Tennessee and were measured on 5 year intervals for 25 years. For the models they evaluated, they used 10-25 year prediction periods. One of the models they used was SETWIGS, part of the southern variant of FVS (Dixon 2002). They came to the conclusion that SETWIGS did relatively poorly in predicting southern upland hardwood growth, but it was the best model for predicting southern bottomland hardwood growth. To select bottomland hardwood plots, they limited stand age, site index, and density (stocking percent). Their project led to the following conclusions for SETWIGS: predictions for younger stands are substantially poorer than older stands and stands with lower site index had more accurate growth projections.

Rauscher and Young’s (2000) conclusion about site index agreed with those seen in control charts for the 32 year growth period using the CFI data in FVS. As seen here, Rauscher and Young (2000) also concluded that lower site index plots were more accurately projected (Figure 14 and Figure 15). However, they also concluded that younger stands were less accurately projected than older stands. This does not agree with the results from this study in that the short-term growth predictions were not accurate for some of the CFI re-measurements (Figure 10). They also came to the conclusion that SETWIGS worked relatively poorly for southern hardwood forests, which could be a reason that FVS fails to give accurate projections for the
longest CFI projection. Rauscher and Young (2000) used confidence limit estimations, comparable to this study, but for only one point in time.

The next two sets of control charts were created using only the FIA data and were for subsets of the plot data based on stocking percent and aspect. Control charts indicated that moderately stocked stands were more accurately projected over each time period compared to poorly and fully stocked stands. Control charts limited to plots from north and south facing slopes respectively showed that plots on north facing slopes were more accurately projected than plots on south facing slopes (Figure 22 and Figure 23). This could be caused by below average annual precipitation in 6 of the 10 years in the sample period (Figure 1). South facing slopes received more sunlight than north facing slopes and were typically hotter resulting in less available water (Colbert et al. 2002). In contrast north facing slopes were cooler resulting in moister soils compared to south facing slopes. Control charts created by limiting stocking percent and slope aspect if input data indicated that growth model accuracy was affected by both of these factors and that changes in annual precipitation combined with aspect may affect model accuracy.

Colbert et al. (2002) examined the effect of aspect on tree growth, the interaction of precipitation and aspect, and the response to drought for four hardwood species in the Appalachian Mountains of West Virginia. The species studied were yellow-poplar (Liriodendron tulipifera L.), northern red oak (Quercus rubra L.), chestnut oak (Quercus prinus L.), and red maple (Acer rubum L.), all of which were found in the oak/hickory forest type used here. Colbert et al. (2002) used southwest and northeast aspects. Their study found that all species except northern red oak showed significant differences in growth between different slopes and different aspects (P<0.05). All the species but chestnut oak exhibited higher growth rates on northeast slopes (Colbert et al.
Red oak, chestnut oak, and red maple only showed a mild response to below average precipitation while yellow poplar growth declined sharply (Colbert et al. 2002). The interaction of precipitation and aspect with drought conditions showed little evidence that oak species were affected by drought conditions on the southwest facing slopes (Colbert et al. 2002). The yellow-poplars had a greater response to drought conditions with decreased growth (Colbert et al. 2002). The aspect limited control charts for south facing slopes and north facing slopes were in control for all re-measurement periods even through there were 6 years of below average rainfall (Figure 22 and Figure 23). However, as Colbert et al. (2002) indicated oak trees were less sensitive to drought conditions. Growth decline due to drought in the eastern United States has been shown to last only a few years (Cook and Jacoby Jr 1977). Even with growth decline due to drought conditions, growth recovery was found to be rapid (Orwig and Abrams 1997). Control charts limiting slope and aspect indicated these variables did not affect the accuracy of the growth projections for FIA data.

The average annual precipitation for Tennessee from 1960 to 2009 was 49 inches (Figure 2). Twenty-three of the years were below average in annual precipitation, while 27 years were at or above average. Prolonged drought periods that could have affected forest growth were between 1985-1988, 1999-2001, and 2005-2008 (Figure 2). After each of the periods of drought years, annual precipitation increased well above average.

The southern pine beetle epidemic from 1999-2002 was the worst in Tennessee since the 1970s (Oswalt et al. 2004). To see how this may be reflected in control charts the CFI data were separated into plots that consisted of mixed hardwoods with pines and plots the consisted of hardwoods with no pine from the 1977 survey. Only one re-measurement plot in 2009 contained
any pine. The control charts indicated that plots that had pine located on them in 1977 were more accurately projected (Figure 24). The growth prediction equation used for WinYield included just upland oaks while FVS included equations specific to the oak/hickory group. There are separate equations for hardwoods mixed with pine in both FVS and WinYield, but they were not used in this study because the plots consisted of southern hardwoods at the last re-measurement period. The control charts limiting species composition indicated that control charts could be a useful tool in evaluating what factors affect model accuracy.

Roesch and Van Deusen (2010) presented control charts as a tool to evaluate forest growth and deviations from past data in annual forest inventories. They provided an example using annual FIA data from Alabama and Georgia from 1997 through 2007 that combined data over previous years to compare to the next years data. The data consisted of pine plantations and natural stands and were divided into FIA panels and EcoClass. Roesch and VanDeusen (2010) concluded that control charts were a simple and useful way to evaluate forest inventory data.

The FIA data were on a landscape spatial scale covering plots in Alabama, Georgia, and Tennessee while the CFI data were on a much smaller scale representing a typical forest inventory on three tracts in the Cumberland Mountains of Tennessee. Only the shorter interval projections (<8 years) were used to compare spatial scales because there were no long interval FIA projection periods. Controls charts indicated that the shorter interval projections were in control for both spatial scales at all prediction periods (Figure 7 and Figure 8). However, the control chart for the landscape scale FIA data determined that the projections were more consistent over each time period because the predictions for FVS and WinYield had close to the same error for each time period, which could be from the larger sample size. The larger scale
FIA data set consisted of total of 728 plots with each re-measurement year having a different number of plots (Table 5) while the CFI data set only had 48 plots each year.

The FIA data were limited to plots with limited mortality and no harvest. The study by Watson (1979) on the CFI data found that the Wilson Mountain tract had an increase in mortality from 1972-1977 and that the mortality rate for this interval was higher than the in-growth rate. The control charts indicated decreased model accuracy due to mortality. Control charts indicated that growth was accurately predicted at both spatial scales, but the models were more accurate at the landscape scale. Only the CFI data set had a long interval projection (32 years). For the CFI data the short interval projections were accurate while the long interval projections were inaccurate. Control charts showed that growth was accurately projected at short temporal scales, while long temporal scales are more likely to be inaccurately projected. Control charts can be utilized to determine forest growth model accuracy at different spatial scales and temporal scales, but may be more sensitive for smaller data sets.

Control charts were practical for determining if forest growth and yield models were accurate. However, a number of other model evaluation techniques do exist. Some of the other model evaluation techniques include: hypothesis testing, general linear model, regression analysis, or sensitivity analysis. General linear models present model based statistics that help analyze how well a model variable fits to the model (Gardner and Turner 1991). This method uses hypothesis testing, goodness of fit, and ANOVA tables to evaluate how well variables fit a model. Soares et al. (1995) indicated that one simple and efficient way to evaluate a model was using linear regression of observed versus predicted data. Linear regression will determine the quality of the predictions through the $R^2$ and the slope of the fitted line. Sensitivity analysis is another model
evaluation technique that has been used to determine the degree of response, or sensitivity of changes in model components (Grant and Swannack 2008). Sensitivity analysis helps determine the variables and parameters that most affect the model outputs. However, all of these and many other model evaluation techniques only involve examining the model or its outputs at one point in time. In contrast, control charts can represent multiple points in time in one analysis. Control charts visually indicated if a model was increasing or decreasing accuracy over time. Other model evaluation methods may be optimal for determining what exactly was causing a model to become inaccurate. However, determining when such evaluations are necessary in light of long term changes in growing conditions would be greatly simplified using control charts. With control charts it was possible to determine that for the FIA data, the models had no apparent trends in model accuracy over large spatial extents and short growth periods. However, for the smaller spatial extent and the one long growth period for the CFI data, both models gave inaccurate predictions. This result suggests that further evaluation was warranted to determine if the models simply would involve doing separate analysis for each point in time and then comparing each point in time separately. All the evaluation techniques are useful and effective in modeling accuracy, but control charts are more practical in modeling forest growth overtime.

When comparing data over time, control charts can be a useful method because they incorporate the data at every time period being evaluated or monitored and project it in a chart. Control charts visually show any points in time that may be inaccurate or getting closer to inaccuracy over time. Any kind of process or monitoring over time can be evaluated using control charts because of the fact that control charts incorporate all the time periods in one chart. However, if individual variables, or time periods need to be evaluated, control charts would not be the best
method. Control charts only determine when a process goes out of control and becomes inaccurate and they do not test what causes the process to become out of control. They help identify trends in data over time. Other statistical tests like ANOVA tables, goodness to fit tests, hypothesis tests, linear regression, or sensitivity analysis can be used to test and evaluate the inaccuracies of individual variables in the model or process.
Literature Cited
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Richard Cristan is from Elysburg, Pennsylvania. He attended the University of Tennessee-Knoxville, where he earned a B.S. in forest resource management and a minor in wildlife and fisheries science. He worked with the Tennessee Division of Forestry- Forest Inventory and Analysis program as an intern the summer prior to his graduation.