

MODELING WITHIN-TREE CHANGES IN
WOOD SPECIFIC GRAVITY AND MOISTURE CONTENT
FOR LOBLOLLY PINE IN GEORGIA

by

KRISTEN MICHELLE PHILLIPS

(Under the Direction of Richard F. Daniels)

ABSTRACT

The forest industry is eagerly adopting increasingly intensive silvicultural treatments, such as genetic improvement, complete weed control and multiple fertilizations, for its plantations in order to meet timber production demands. Such intensive treatments increase overall wood quantities; however, their effects on wood quality are not well known. A strong base of information on the wood properties of loblolly pine has been compiled in this study. This information was used in a search for individual tree models that describe as well as predict wood properties within a tree. Prediction models were developed for specific gravity and moisture content, two wood properties which are important measures of wood quality. This allows for the incorporation of quality and value variables into loblolly pine growth and yield prediction systems. Timber growers will be able to use these models in order to compare wood quality values between various silvicultural management regimes.

INDEX WORDS: Loblolly Pine, Specific gravity, Moisture content,
Prediction models, Wood quality

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B.S., Clemson University, 1999

A Thesis Submitted to the Graduate Faculty of The University of Georgia in
Partial Fulfillment of the Requirements for the Degree

MASTER OF SCIENCE

ATHENS, GEORGIA

2002

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DEDICATION

To everyone who helped me finish my thesis at UGA. To all of my friends and family, who supported and encouraged me, especially my mom and dad, Gramma and Papa, sister and brother, and Aunt Susie. To all of my best friends, who helped push me to the finish, including Jamie, Quintina, Kristin, Agatha, and Salli. And, to my loving fiancé, John Lee Thomson, who listened to all of my modeling woes over the past 2 years.

ACKNOWLEDGMENTS

Thanks to everyone at the University of Georgia and Daniel B. Warnell School of Forestry for two great years. Thanks to Dr. Richard F. Daniels, my major professor, for his time and consideration. I would also like to thank Dr. Bruce Borders and Dr. Robert Teskey for serving as committee members spending time with me. Special thanks to Chuck Rose for all of his time, help and ideas. Thanks to Hector De Los Santos for all of the extra explanations and computer help, and Mike Harrison for the SAS help. Finally, thanks to the UGA Wood Quality Consortium for providing data and the Georgia Tradition Industries Program for providing financial assistance.

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CHAPTER 1

INTRODUCTION

The forest products industry in the southern United States faces great challenges regarding the future fiber supply. A growing shortage of large timber from old growth softwoods, more restrictive environmental policies, and changes in land use have led to increased wood production from less land (Daniels 1999). Increasing costs of forest ownership and management along with improved cultural practices are encouraging short-rotation, intensive forest management to increase growth rates and shorten investment periods (Zhang 1997). There is concern, however, that young fast-growing plantations produce low quality wood with high proportions of juvenile wood (Clark 1997).

The forest products industry is relying more on fast-grown plantation wood; so, it is increasingly important to assess precisely the physical and mechanical properties of this new wood supply (Zhang 1997). Approximately 30 percent of the South's softwood growing stock is currently in plantations (Clark 1997). Georgia could see a 46 percent increase in acreage of pine plantations, from nearly 6.4 million acres in 1995 to 9.3 million acres in 2040 (Wingfield 2001). These projections are based on consistent demand for forest products and continued high rates of growth of pine plantations throughout the South (Wingfield 2001).

The forest industry is eagerly adopting increasingly intensive silvicultural treatments for its plantations, including genetic improvement, complete weed control and multiple fertilizations, in order to meet timber production demands (Clark 1997; Daniels 1999). Research has shown that these management practices can increase wood yield on a typical southern pine plantation from 5 to 8 m³/hectare/year to 20 to 25 m³/hectare/year (Clark 1997). These growth rates compare well with the fastest growing loblolly pine anywhere in the world. Such intensive treatments increase overall wood quantities; however, their effects on wood quality are not well known. Naturally, the forest industry is concerned about the properties of fast-grown wood; yet, very little is known about the basic wood properties of plantations, even those currently being harvested.

Wood quality is extremely responsive to silvicultural manipulation (Zobel 1984). The southern pine wood industry must understand the impact of silvicultural practices on wood properties in order to produce fast-growing plantation wood with quality the market demands (Clark 1997). To understand the value of increased timber volumes from intensively managed stands, a thorough understanding is needed of basic wood properties, such as specific gravity and moisture content, and their response to the effects of environmental conditions, geographic location, and silvicultural treatments.

Loblolly pine (*Pinus taeda* L.) is the most important fast-growing species planted among the 12 southern states (Clark 1997). A two-year study was implemented to fill the information gap on the basic wood properties of loblolly

pine plantations in Georgia (Daniels 1999). It is the first statewide attempt to establish a baseline of loblolly pine wood properties in relation to environmental and silvicultural conditions. The study was designed to address three objectives. 1) Review the existing literature on basic wood properties. 2) Determine wood properties for existing plantations. 3) Develop models that predict wood properties for loblolly pine, so that wood properties can be factored into growth and yield management models.

Forty-one plantations at or near rotation age, spanning a range of locations, sites and growing conditions across Georgia have been characterized, measured, and sampled for basic wood properties including specific gravity, moisture content, fiber length, coarseness, and microfibril angle. Relevant results of the first two objectives were utilized to progress to the final objective, model development. In this study, modeling research was restricted to specific gravity and moisture content.

Specific gravity is a useful index for the suitability of wood for many important uses (Koch 1972). To standardize comparisons of products and estimation of product weights, specific gravity is used as a standard reference (Forest Products Lab. 1974). The traditional definition of specific gravity is the ratio of the density of wood to the density of water at a specified reference temperature. Since it is closely correlated with the mechanical strength of wood, specific gravity is used as a primary factor in the segregation of high-strength lumber, poles, and pilings (Koch 1972). Specific gravity also largely determines

pulp yield from a given volume of wood. For example, a cord of high-specific gravity (*i.e.* 0.45) southern pine may yield about twice as much kraft pulp as an equal volume of low-specific gravity (*i.e.* 0.38) wood from the same species. Because of its importance to strength and yield, specific gravity can be used as a general measure of wood quality.

Moisture content is another wood property that is informative about the wood quality of an individual tree. Physical and mechanical properties, resistance to biological deterioration, and dimensional stability of any wood-based product are all affected by the amount of water present in the wood (Haygreen 1996). It is important to understand the nature of water in wood and how it is associated with its microstructure and properties since almost all properties of wood and wood products are affected by it. Moisture content is a measure of the amount of water in wood or a wood product (Koch 1972). It is usually expressed as a percentage of the oven-dry weight of wood.

A strong base of information on wood properties of loblolly pine has been compiled in this study. Individual tree models were developed to describe as well as predict these wood properties within a tree, in order to incorporate quality and value variables into loblolly pine prediction equations. As early as 1963, Lane noted the need for timber quality standards. “Much attention is focused on measuring the volume of trees and logs – too little on their quality. In predicting profit margins, errors in judging timber quality can exceed errors in estimating log volume or operation costs.” The models developed in this project

can help timber industry adjust timber values according to wood quality. While higher timber prices cause difficulties for product manufacturers, they create opportunities for timber growers who can justify investments in timber management, which may in turn affect size and quality of timber available in the future (Briggs 1997). Hence, the net worth of value-added products may offset the cost of additional management practices, encouraging higher quality timber.

The challenge for the future is ensuring that the product characteristics meet market requirements (Cown 1997). Industry is steadily moving towards concentration on supplying products which are adapted to well-defined end-uses (Thornqvist 1997). Most difficult, at the present time, is the ability to direct the right log to a defined end-product while still in the forest. Wood quality models can provide valuable information about standing trees.

In this project, individual tree models were developed to describe how specific gravity and moisture content change within individual trees, from stump to tip, for loblolly pine in Georgia. These models allow measures of wood properties and quality to be added to current forest yield prediction systems. These models will provide the basis for comparing properties from tree to tree, within a stand, and among stands under varying environmental conditions.

The main objective of this study is to predict average cross-sectional specific gravity and moisture content from stump to tip in relation to height and diameter for loblolly pine in Georgia.

Specific study objectives include the following:

1. To investigate the patterns of average specific gravity and moisture content by height up the tree and upper stem diameter.
2. To develop predictive individual tree models describing specific gravity and moisture content as a function of height and as a function of diameter.
3. To examine and refine these models with the use of model comparison criteria (R-square/Fit Index and MSE), actual versus residual plots, residual versus predictor variable plots, F-tests for significant differences between regions and site index classes, and stochastic parameter estimation.

CHAPTER 2

LITERATURE REVIEW

Wood quality is an arbitrary term that applies to certain wood characteristics that can be quantified, analyzed, and used to evaluate a final wood product (Larson *et al.* 2001). Wood quality is generally defined by its end-product use (Cown 1997).

Wood from young, fast-growing plantations has a higher proportion of juvenile wood than wood from older, natural stands (Forest Prod. Res. Soc. 1986). Juvenile wood is produced near the center of the tree and is related to the number of rings from the pith, and proximity to the tree's crown when the wood is formed (Zobel 1984). It is commonly defined as the zone of wood extending outward from the pith where wood characteristics undergo rapid and progressive changes in successively older growth rings (Larson *et al.* 2001). In southern pine, the juvenile core usually consists of 5 to 15 growth rings (U.S.D.A. Forest Service 1992). Plantation grown trees have a greater proportion of juvenile wood than naturally grown trees. Plantation grown trees often have controlled density and are planted at wider spacing. They also maintain larger crowns for a longer period of time. Thinnings from plantations less than 15 years old may

consist of nearly all juvenile wood. The tops of all trees, plantation or naturally grown, contain mostly juvenile wood.

The anatomical, chemical and physical properties of juvenile wood are considered less desirable for most forest products (U.S.D.A. Forest Service 1992). Compared to mature wood, it has a lower percentage of latewood, lower specific gravity, shorter tracheids with larger fibril angles, and occasionally disproportionate amounts of compression wood, distorted grain patterns, and pitch deposits (Larson *et al.* 2001). It has low specific gravity due to large diameter cells with thin cell walls (U.S.D.A. Forest Service 1992). Alpha-cellulose is organized in string-like structures, called microfibrils, within the cell wall. In mature wood, the microfibrils are nearly parallel to the long axis of the fibers. In juvenile wood, the microfibrils are not parallel and angles up to 55 degrees may be formed. With increasing microfibril angle, tensile strength in the long axis of the fiber decreases and longitudinal shrinkage and swelling increase. Finally, juvenile wood has lower cellulose and higher lignin content than mature wood. It should be noted, however, that the cellulose content of juvenile wood is quite variable, ranging from 5.7 to 13.7 percent.

The major differences between juvenile and mature wood are strength, specific gravity, and moisture-related dimensional stability (U.S.D.A. Forest Service 1992). These properties greatly influence the grade and quality of solid wood and composite products. Specific gravity is particularly important in pulp manufacture because low specific gravity wood results in low pulp yield and

high manufacturing costs. High percentages of juvenile wood cause building products to be weaker (Bendtsen and Senft 1986) and more prone to warp, creating problems for manufacturers (Quarles and Erickson 1987). Juvenile wood is not of top-quality for manufacturing board and box paper (Zobel 1984). Paper produced from juvenile wood has satisfactory tensile, burst, fold strength and sheet smoothness, but lower tear index and opacity than paper produced from mature wood pulp (Zobel *et al.* 1976).

Earlywood is the portion of the annual growth ring that is formed during the early part of the growing season; it is usually less dense and weaker mechanically than latewood (For. Prod. Lab. 1974). Latewood is the portion of the annual growth ring that is formed after the earlywood has ceased. Wood quality and specific gravity variations associated with earlywood and latewood significantly affect paper quality (Zobel and Blair 1976; Zobel *et al.* 1978). The effects of juvenile wood and earlywood on wood quality may be taken into account with the prediction of specific gravity. High proportions of juvenile wood and earlywood yield lower specific gravity values.

Young and small trees have all of the quality problems and characteristics listed above for juvenile wood. They have other poor characteristics as well. Young trees have greater amounts of reaction wood, producing pulp with lower yields and lower strength properties as well as unstable boards and plywood (Zobel 1984). The increased reaction wood is not desirable for any product. Young timber has poor utility for solid wood and fiber products caused by

shorter fibers, flatter fibril angles, higher lignin, and gelatinous fibers with high cellulose content. These young trees also have higher moisture content. Therefore, purchasing timber by green weight or volume results in handling a large amount of water relative to the amount of dry wood substance available for manufacture. The moisture content of the young wood in the top of a loblolly pine tree may contain nearly twice the amount of water per unit volume as does wood from the base of the same tree (Britt 1970).

Forest managers are attempting to offset demand pressure using silvicultural and genetic manipulation, which tend to change wood quality. Wood characteristics, especially wood specific gravity, are responsive to improvement through genetic manipulation. Silvicultural actions that alter tree growth can also affect wood quality (Zobel 1984). Forest managers need some type of measurement of wood quality in order to compare differences in treatments, improve management decisions, and accurately evaluate timber products.

Basic wood properties of southern pine vary significantly across Georgia. Faust *et al.* (1999a) show that intensively managed pine in north Georgia had significantly lower wood specific gravity and shorter fiber lengths than intensively managed pine in south Georgia and north Florida. In addition, dimension lumber from intensively managed loblolly pine in the Georgia Piedmont had strength and stiffness values below the specified visual lumber grade (Clark *et al.* in process; Faust *et al.* in process). There is a need to describe

the reasons for these types variation so that it can be predicted and applied to forest management decisions.

Specific Gravity

As noted previously, specific gravity can be used as an efficient indicator of wood quality. Megraw (1985) states: “Of all the parameters practical to measure, specific gravity is recognized as the most useful index to predicted physical behavior of wood.” It is of key importance in forest product manufacturing because it has a major effect on both yield and quality of fibrous and solid wood products; it is also altered by silvicultural and genetic manipulation (Zobel & van Buijtenen 1989). Therefore, specific gravity largely determines the value and utility of wood, overshadowing the importance of many other wood properties.

Wood specific gravity is the ratio of two densities: the density of wood to the density of pure water at 4° Celsius (Koch 1972). Wood density is the weight (mass) of wood per unit volume. In the English standard system of measurement, the density of water is 62.43 pounds per cubic foot. Thus, the density of wood in pounds per cubic foot is 62.43 times the corresponding value for specific gravity. In the metric system, the density of water can be considered equal to 1 gram per cubic centimeter (gm/cm^3). So, the specific gravity of a wood substance becomes numerically equal to its density. The range of specific gravity

to be expected in loblolly pine is approximately 0.38 to 0.56. The specific gravity of wood is dimensionless and independent of the units used in its computation.

Since specific gravity is based on density, it is necessary to indicate the measurement conditions for specific gravity (Koch 1972). Specific gravity is calculated using oven-dry weight or mass (Haygreen 1996). Volume may be determined at any moisture content; that moisture content must be specified. For this project, specific gravity was determined based on the density of wood, oven-dry weight divided by green volume.

Many factors affect specific gravity including site, climate, geographic location, and species (Haygreen 1996). It is difficult to separate the independent effects since many of these factors occur in combination. Inconsistencies throughout the large amount of scientific literature dealing with these relationships indicate the complexity of their interactions.

Site-related factors including moisture, availability of sunlight, nutrients, wind, and temperature also affect specific gravity (Haygreen 1996). In turn, these factors are determined by elevation, aspect, slope, latitude, soil type, stand composition, soils, drainage, and spacing. These factors can affect the size and wall thickness of the cell, hence affecting the density. Sensitivity to each factor differs greatly for each species.

Specific gravity varies significantly within a tree (Haygreen 1996). In many species, butt logs have higher density than logs cut from higher in the

stem. In softwoods, the density decreases with height in the tree and increases with distance from the pith.

When considered on a cross-sectional disc basis as a function of height, many studies have produced specific gravity curves for loblolly pine, which are very similar to Figure 4.1. It is obvious that specific gravity is highest near the base of the tree, decreasing much faster with increasing height within the first 4.5 feet than at the upper heights. Therefore, butt log segments have a much greater specific gravity gradient from one end to the other than do upper log segments. This must be accounted for in models used to represent specific gravity within trees.

Since all tree populations, regardless of environmental and silvicultural conditions, can be classified according to age, growth rate, and geographic location, it is useful to examine variation of specific gravity within species as related to these three factors.

Age. Within the first few rings, near the stump, specific gravity in southern pine wood has a strong positive correlation with age. This trend is confined to wood near the pith, and old trees do not necessarily have higher specific gravity than young trees (Koch 1972). On the other hand, data have been published indicating a strong positive correlation between stand age and tree-average specific gravity. In an analysis of loblolly pines growing in the Coastal Plain of South Carolina, trees in stands 15, 30, and 45 years old had tree-average

specific gravity of about 0.41, 0.46, and 0.48, respectively (Zobel *et al.* 1965); older loblolly pines contain higher proportions of mature wood.

Growth Rate. It should be noted that growth rate of plantation trees, when manipulated by changing environmental or silvicultural conditions, may not be closely correlated with wood specific gravity (Koch 1972). Yao (1970) completed a study of 40 loblolly pines, aged 31 to 76 years, cut on a 160-acre tract in Mississippi, which related growth to specific gravity. After considering all heights and radial positions, he concluded that wood specific gravity was positively correlated with number of rings per inch in the range of 3 to 8 rings per inch and specific gravity was generally unrelated to growth rate in wood with more than 8 rings per inch. If tree-average specific gravity was measured throughout the natural ranges of southern pine species, it would probably have a weak negative correlation with width of growth rings at breast height (Koch 1972).

An inherent relationship between growth rate and specific gravity is not evident (Megraw 1985). Fast growth rate does not necessarily imply lower specific gravity. However, if faster grown trees are harvested at an earlier age because they reached a certain average diameter sooner, they will produce lower specific gravity products. They will contain fewer rings from the pith at any given height compared to older trees with the same diameter. This is due to the large juvenile core. Beyond the juvenile core, proportions of latewood and earlywood are often similar for fast and slow grown trees. However, when a

larger juvenile core is present, as in fast grown trees, the overall amount of latewood may be less, leading to lower specific gravity (Larson *et al.* 2001).

Geographic Location. Variation due to geographic location must be included in predictive models. Several studies have shown a tendency for specific gravity to increase slightly with decreasing latitude (Megraw 1985). This may be due to the fact that longer growing seasons produce more latewood. It has also been shown that moisture deficiencies and major soil differences cause regional specific gravity differences. For loblolly pine, specific gravity values are higher on average in the Gulf Coastal region and Atlantic Coastal regions than in inland areas. Specific gravity values increase from north to south, particularly in the western part of the range, Midsouth, and along the Atlantic Coast, but not in the Piedmont region of North Carolina, South Carolina, and Georgia.

Within tree variation. It is also important to consider variation within-tree, within annual increment, and within position in the tree. Specific gravity, within an individual tree, varies across each annual ring, between adjacent rings, with radial position in the stem, and with height above the ground (Koch 1972).

There are distinct specific gravity differences between earlywood and latewood, across annual increments. Latewood in southern pines is two to three times as dense as earlywood (Koch 1972). Many studies of southern pine have shown a positive correlation between specific gravity and the percent of latewood. The relationship between specific gravity and the earlywood-to-latewood ratio within individual growth rings in southern pines is largely

dependent upon the amount of wall thickening of individual cells. Wall thickening has been linked to nutrition and the availability of photosynthates.

Specific gravity of stemwood is a function of the densities of earlywood, latewood, and the relative proportion of each in the wood (Koch 1972). All three of these factors vary with radial distance from the pith and with height in an individual tree. The specific gravity of earlywood is negatively correlated with number of rings from the pith (Taras 1965). Latewood specific gravity shows a positive correlation with age during the first 10 years or so and then levels off. Specific gravity of the combined earlywood and latewood increases sharply with radial distance from the pith until ring 5 to 10, continuing to increase slowly until about ring 30. Specific gravity changes very little beyond age 10 to 15 (Koch 1972). Ring specific gravity of entire rings is negatively correlated with height if sampled at a constant number of rings from the pith (Taras 1965).

Moisture Content

Wood is a hygroscopic material. Its volume and weight varies in response to the gain or loss of water molecules. Therefore, the moisture content at which weight and volume are determined must be clearly stated when either terms of specific gravity or density are used with reference to wood (Megraw 1985).

Live southern pines commonly contain approximately 1 pound of water for each pound of dry wood (Koch 1972). Since many of the desirable properties of wood are negatively correlated with its moisture content, wood generally

serves best if most of this water is removed. As in this study, moisture content is usually expressed as a percentage of the oven-dry weight of wood.

Percentage moisture content

$$= \frac{(\text{weight of wood with moisture} - \text{oven-dry weight of wood})}{\text{oven-dry weight of wood}} \times 100$$

The oven-dry weight is measured after drying the wood to a constant weight in an oven held at 101° to 105 ° Celsius.

In southern pine, moisture content of wood varies among species, within species, and within trees.

Variation among species. Comparisons among species are most valid for trees of the same age (Zobel 1976). Table 2.1 provides tree-average moisture content estimates, defined above, for six southern pine species at age 30 (Koch 1972).

Table 2.1 Moisture content of wood in stems of 30-year-old living pine trees (Koch 1972).

Pine species	Moisture content Percent
Loblolly	110
Longleaf	100
Shortleaf	110
Slash	90
Spruce	120
Virginia	100

Variation within species. Moisture content of standing southern pines has an inverse correlation with tree age (Zobel 1976). Young trees have higher moisture contents than older trees, given that juvenile wood has a much higher moisture content than mature wood. Moisture content also has an inverse correlation with specific gravity. Wood attains its maximum moisture content when the cell walls and lumens are completely filled with liquid water (Simpson 1993). When specific gravity is high, lumen volume is low; therefore, maximum moisture content is restricted. In other words, maximum moisture content for dense wood is lower because the voids are smaller and fewer in dense wood. Koch (1972) did not find evidence of significant relationships between moisture content and growth rate or season of the year.

Genetic differences can cause variation in moisture content among trees of the same species. Large tree-to-tree variation exists among individuals of the same site, species, and age; however, these differences tend to be consistent by family. Parents with low moisture content tend to produce progeny with low moisture content (Zobel 1976).

Variation within trees. Moisture content varies with radial position and height above ground (Koch 1972). The amount of heartwood is a contributing factor. Heartwood has a much lower moisture content than sapwood. This variation is also affected by the amount of extractives. Pine with a large amount of extractives has relatively low moisture content. For example, resinous

heartwood may have less than 20 percent moisture content, while sapwood at the same height has 90 percent moisture content (Zobel 1976).

Due to the inverse relationship between moisture content and specific gravity, latewood in living pine sapwood should have a lower percentage of moisture than earlywood (Koch 1972). As with specific gravity, the dominant factor affecting the variation in moisture content is the amount of juvenile wood. In general, juvenile wood has a higher moisture content than mature wood. In loblolly pine, juvenile wood of young trees has substantially more moisture per unit of dry wood weight than mature wood (Zobel 1976). The relationship may be reversed in older trees, after the formation of heartwood (Koch 1972).

In southern pine, moisture content is positively correlated with height above ground (Koch 1972). Moisture content at breast height is closely correlated with tree-average values (Zobel 1976). This relationship is best when data are taken from wedges cut from cross-sectional disks (Koch 1972). So, breast-height increment cores can be used to obtain acceptable estimates for tree-average moisture content.

Taper Equations

The term *taper* is used to describe the profile of decreasing stem diameter with increasing height up the stem (Clutter *et al.* 1983). Taper equations express the expected diameter as a function of height above ground level, total tree height, and diameter at breast height. These equations are useful adjuncts to

merchantable volume equations, estimating merchantable volume up the stem. Using the information in a taper equation, the area under a curve of cross-sectional area plotted against the height can be determined; this area represents the volume of the tree bole. In other words, the volume of the bole can be determined by integrating a taper function. The major advantage of using integrated taper equations, as opposed to volume equations, is the flexibility of estimating volumes to variable upper stem diameter limits from one function.

Many advanced taper equations have been developed for loblolly pine and all other southern pine species. Weight prediction equations, which predict weight to different diameter limits have been derived using the integral of the taper model and a wood density equation. Bailey and Fang (2000) and Zhang *et al.* (in press) used a simple linear model to describe specific gravity as a function of height above ground and age, proposed by Parresol and Thomas (1989, 1996). In this project, more complex models for specific gravity were investigated including nonlinear models, which may be better able to capture the shape of the relationship between specific gravity and height.

CHAPTER 3

METHODS

Field Data Collection

The following field procedures were completed by the University of Georgia and the U.S. Forest Service field crews during the summers of 1999 and 2000. Forty-one operational loblolly pine plantations, 20-25 years old, were sampled primarily across Georgia to determine basic wood properties. The sample was intended to represent the types of plantations being harvested currently, and was designed to define a baseline for later comparisons for more intensively managed plantations. Plantations were sampled in each physiographic region (Figure 3.1): Piedmont (14), Upper Coastal Plain (13), and Lower Coastal Plain (14). Plantations in each region were classified with site indices greater than or equal to 65 (base age 25) or site indices less than 65. Four stands were sampled outside of the state along the Georgia border, two in the Piedmont of South Carolina and two in the Lower Coastal Plain of Florida.

The stands selected for sampling were located on land owned by forest industry companies, and included only stands with similar silvicultural history: 1) site preparation with no herbaceous weed control; 2) no fertilization at

Stand Locations

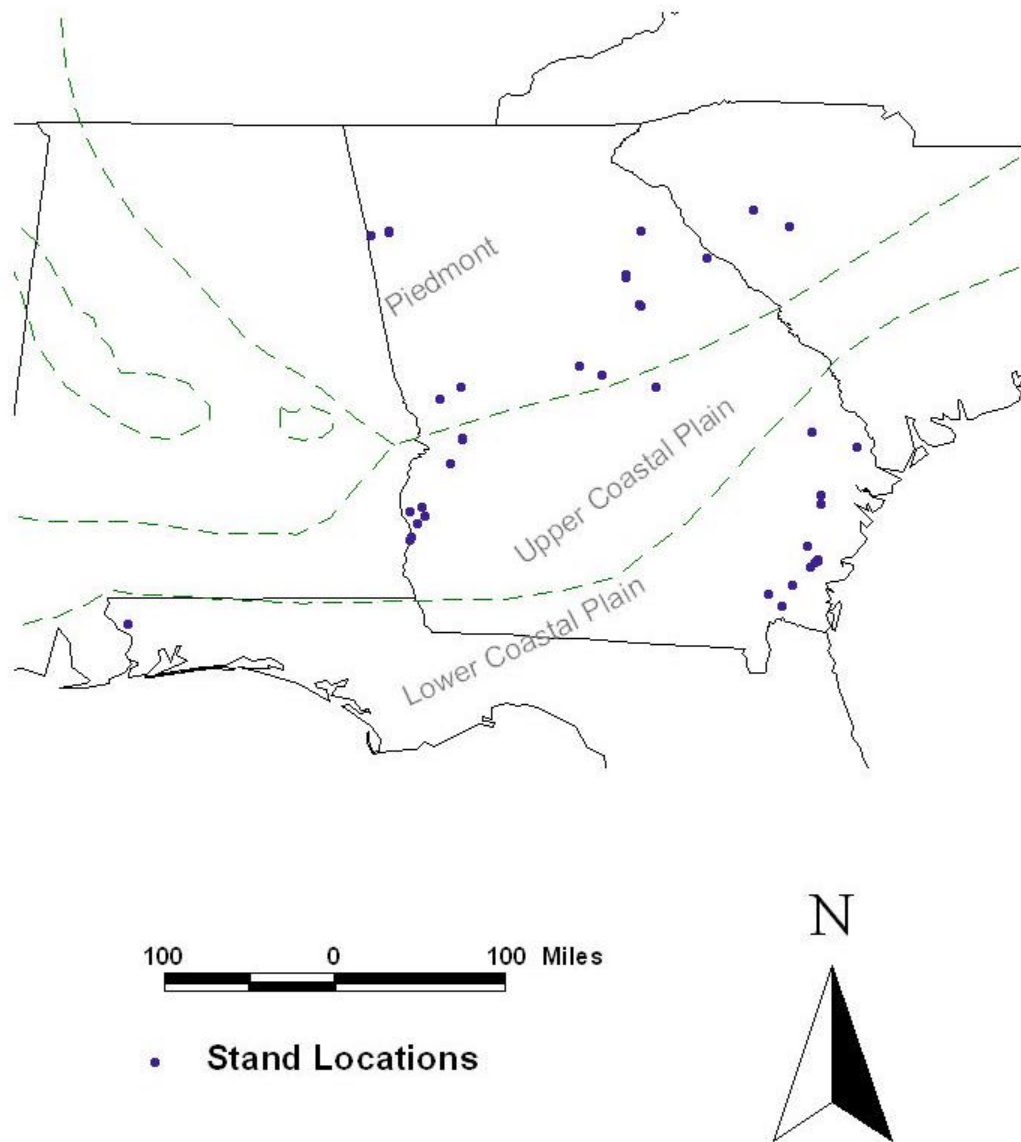


Figure 3.1. Stand location map for the 41 operational loblolly pine plantations sampled summers of 1999 and 2000.

planting except Phosphorus on Phosphorus-deficient sites; and, 3) stand density of at least 250 trees per acre. Trees larger than five inches in diameter were inventoried on three 1/10-acre plots by species, dbh (diameter at breast height, 4.5 feet), total height and tree grade to determine stand density and diameter distribution. A sample of 30 trees, selected proportionally to the diameter distribution in each stand, was cored at 4.5 feet (1.37 meters) high using a 12 mm (0.47 inch)-increment hydraulic borer. Three of the bored trees on each plantation, 123 total, were felled for disk samples used to determine wood properties up the bole. Each plot center was documented using the geographical positioning system (G.P.S.). Average stand characteristics are summarized in Table 3.1.

Table 3.1. Average stand characteristics for felled trees by physiographic region.

Region	Stands Sampled (No.)	Site Index (Base Age)
Lower Coastal Plain	14	78.92 (59.16 - 88.73)
Upper Coastal Plain	13	65.76 (51.35 - 80.99)
Piedmont	14	59.66 (50.52 – 70.63)

Felled Tree Analysis

Two 1-inch cross-sectional disks were cut at the stump, 4.5 feet, and 5-foot intervals to a 1-inch dob (diameter outside bark) top. One of the disks from each level was used to determine disk specific gravity, moisture content and weight

per cubic foot. Specific gravity and moisture content were determined based on oven-dry weight and green volume.

Disk specific gravity and moisture content data collected from the felled tree analysis were analyzed. Models were developed to predict disk specific gravity and moisture content, from stump to tip, using total height, disk height, diameter outside bark, and diameter at breast height. Average stand characteristics are summarized in Table 3.2.

Table 3.2. Average tree characteristics for felled trees by physiographic region.

Region	Trees Sampled (no.)	DBH (inches)	Total Height (feet)	Tree Age (years)
LCP	42	9.23 (6.0 – 13.6)	70 (49 – 84)	23 (21 – 25)
UCP	39	9.36 (5.9 – 14.0)	61 (42 – 81)	23 (20 – 25)
Piedmont	42	9.23 (5.7 – 12.6)	58 (44 – 76)	23 (21 – 26)

Model Development

The general approach used to develop and choose the “best fit” prediction model for disk specific gravity and moisture content follows:

?? Information was gathered about potential variables and model forms from literature, past knowledge and other sources.

?? Data were entered into a database.

- ?? The data were imported into SAS for analysis.
- ?? Various graphs of raw data were examined for patterns among variables. Specific gravity and moisture content were plotted against dob, disk height, and relative height to determine the shape and strength of the relationships between these variables.
- ?? Candidate model forms were selected and fit to the data based on patterns of various independent variables versus dependent variables with the most descriptive relationship. If linear models were insufficient, nonlinear models were selected. Potentially useful non-linear models included the Chapman-Richards, various published taper models, the Freundlich model, and others.
- ?? SAS (PROC MODEL) was used to estimate model parameters.
- ?? Regression analysis fit statistics were compared, searching for high R-square (for linear models) or Fit Index (for nonlinear models) and low mean square error (MSE). Actual and residual plots were also studied and compared among models. Simpler models were preferred. Nonlinear models were selected if they had significantly improved regression statistics over those of the linear models.

$$?? \text{ R-square} = \text{Fit Index} = 1 - \frac{\sum_{i=1}^n (Y_i - \hat{Y}_i)^2}{\sum_{i=1}^n (Y_i - \bar{Y})^2} .$$

$$MSE = \frac{\sum_{i=1}^n (Y_i - \hat{Y}_i)^2}{n - p}.$$

where

Y_i = dependent variable of interest

$\hat{Y}_i$ = estimated value of Y_i from the model

$\bar{Y}_i$ = mean value of Y_i

n = number of observations

p = number of parameters.

?? All variables are significant at a maximum p-value = 0.05.

?? All data plots were examined to determine if variability was heterogeneous.

Heteroscedasticity was considered. There was a visual search for patterns in the residuals, to identify patterns of poor fit, outliers and data errors.

?? Indicator variables were used to test for significant regional and site differences: Lower Coastal Plain versus Piedmont and Upper Coastal Plain and site index below 65 versus site index above 65. Full and reduced models were fitted to test these hypotheses using conditional F-tests.

?? After selecting the best model and identifying regional and site index differences, stochastic parameter estimation was used.

According to the data patterns, all practical models are given here as candidate models. These are discussed, in more detail, in the results.

Candidate Models

Specific Gravity = F (Height)

A fundamental question under investigation is that of describing the change in specific gravity up the bole, from the stump to the tip. A prediction equation for specific gravity as a function of height provides the dry weight per unit volume at any height and can be combined with an appropriate taper equation and integrated to provide dry weight estimates to specific height limits (Parresol and Thomas 1996; Zhang *et al.* in press). Specific gravity decreases with increasing disk height (Figure 3.2).

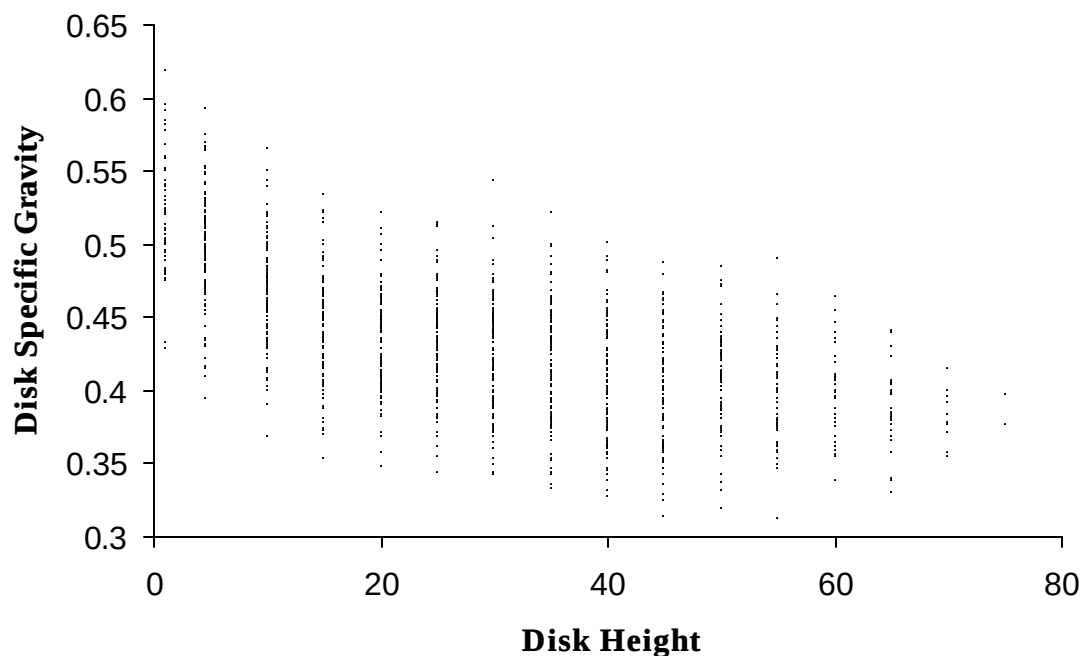


Figure 3.2. Disk specific gravity decreases with increasing disk height.

This pattern is very similar to a taper function (*e.g.* Harrison and Borders 1996), in which diameter decreases with increasing disk height.

$$dob = dbh [(H - h) / (H - 4.5)]^{bo}$$

where

dob = predicted diameter outside bark at height h above the ground

dbh = diameter at breast height

H = total height

h = height above ground

bo = parameter estimated by regression

Equation (1) was adapted from this taper equation, redefined in terms of specific gravity.

$$SG_h = SG_D [(H - h) / (H - 4.5)]^{bo} \quad (1)$$

where

SG_h = predicted specific gravity at height h above the ground ($0 \leq h \leq H$)

SG_D = specific gravity at dbh

Specific gravity versus relative height (Figure 3.3) has an inverse sigmoid shape, which may be modeled by inverting the following form of the Chapman-Richards growth curve with a nonzero intercept (Ratkowsky 1990). This model is often used in forest growth modeling. It is derived from basic biological growth

assumptions and has proven to be very flexible in application (Clutter *et al.* 1983).

$$H = b_0 + b_1[1 - \exp(b_2 \text{Age})]^{b_3}$$

Model 2 is an inverted Chapman-Richards function, in terms of specific gravity and relative height.

$$SG_h = \log [1 - \{(R_h - b_0)/b_1\}^{(1/b_3)}] / b_2 \quad (2)$$

where

R_h = relative height (h / H)

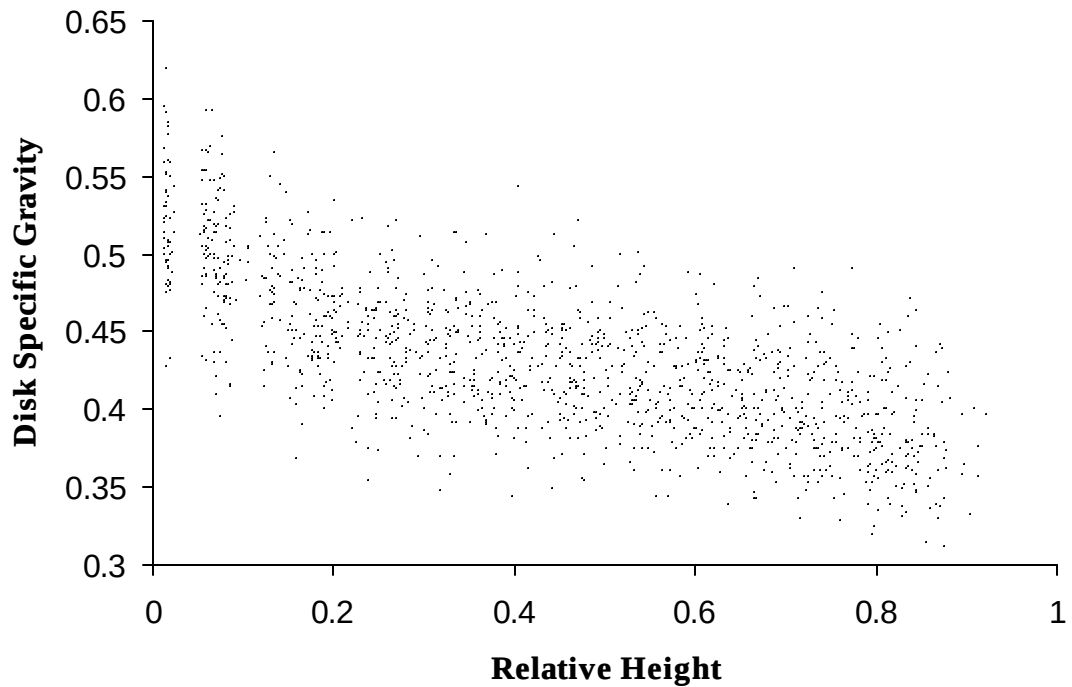


Figure 3.3. Disk specific gravity versus relative height (R_h) has an inverse sigmoid shape.

Several measures of height were considered as the independent variable in these equations, disk height (h), total height (H), total height minus disk height ($H-h$), and relative height (R_h). Relative height (R_h) described the largest amount of variation for specific gravity and has the most homogenous variance properties.

According to the data pattern, a third model (3) was proposed as a candidate model for specific gravity as a function of relative height.

$$SG_h = b_0 + b_1 [\log (R_h^{-b_2} - 1)] \quad (3)$$

This is a three-parameter curve with an inflection point, published by Ratkowsky (1990). This model has proved to have reasonably good estimation properties when tested on several data sets (Ratkowsky 1990).

The simple linear model (4) was also fitted to the data for comparison to the nonlinear models.

$$SG_h = b_0 + b_1(R_h) \quad (4)$$

The fit was unacceptable and considerably below comparison value based on the model selection criteria. Hence, it was determined that a nonlinear model was required for specific gravity as a function of relative height.

Specific Gravity = F (Diameter)

Prediction equations for specific gravity as a function of diameter outside bark can be used to predict specific gravity at any upper stem diameter. The dob

variable describes more of the variation in specific gravity than any other variable or interaction with diameter. It also has more equally distributed variation. There is a large amount of variation in specific gravity as a function of diameter outside bark (Figure 3.4).

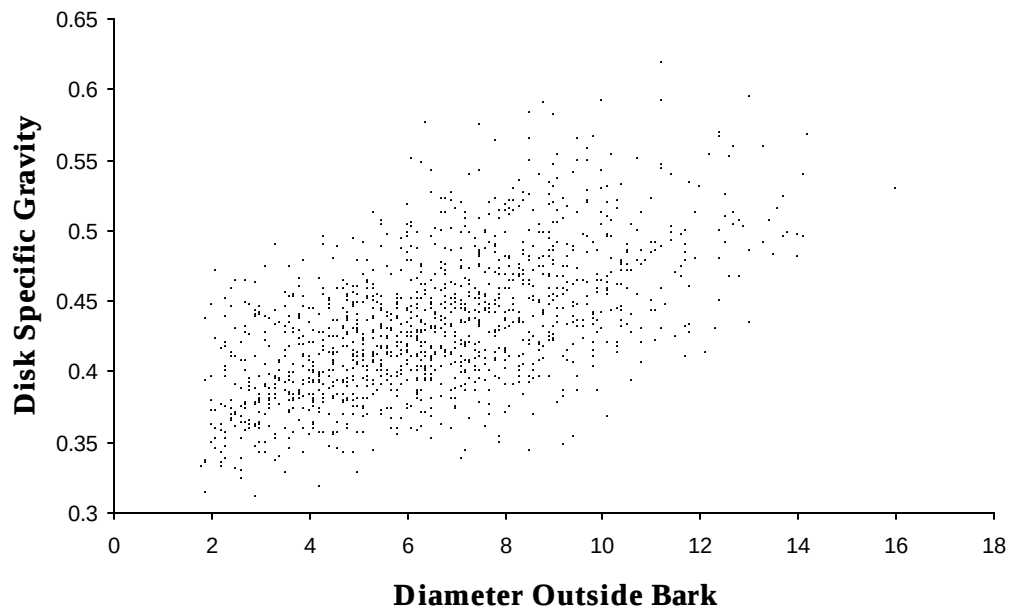


Figure 3.4. Disk specific gravity as a function of dob appears linear.

The relationship appears linear overall, but there are several curvilinear patterns, which can be detected at the individual tree level. A consistent pattern is difficult to identify. Models for the most common data patterns were fit. Model (5) is reasonably close to the linear Freundlich model (Ratkowsky 1990).

$$SG_h = b_0 + b_1(dob)^{b_2} \quad (5)$$

This model takes on various curvilinear shapes based on parameter estimates.

Many types of curvilinear and sigmoid shaped models, including variations of the Chapman-Richards model, from past literature were also evaluated. All models seemed to result in linear predictions. Thus, a linear model (6) was fit to the data.

$$SG_h = b_0 + b_1 (dob) \quad (6)$$

Stem dry weight of wood is equivalent to the product of stem volume of wood and the associated density (d). In other words,

$$W_h = V_h \times d$$

where

W_h = dry weight at height h above the ground ($0 \leq h \leq H$)

V_h = stem volume at height h above the ground ($0 \leq h \leq H$).

Taper equations express expected stem diameter, inside or outside bark, as a function of height above ground, total height and diameter at breast height (Clutter *et al.* 1983). Taper functions effectively predict the stem profile of an individual tree (Sturdza 1999). Along with the equations developed in this project to predict specific gravity as a function of diameter outside bark, these taper equations will be useful for estimating specific gravity up the stem. And,

dry weight (W_h) up the stem can be predicted as the product of volume and density for a given section.

$$\text{Moisture Content} = F(\text{Height})$$

Moisture content prediction equations as a function of height can be used along with an appropriate specific gravity and taper equation and integrated to provide green weight estimates to specific height limits. Moisture content and specific gravity have opposite trends. Moisture content increases with increasing disk height (Figure 3.5). Relative height describes the largest amount of variation in moisture content, compared to all other height variables and interactions. The relationship between moisture content and relative height is slightly curvilinear (Figure 3.6).

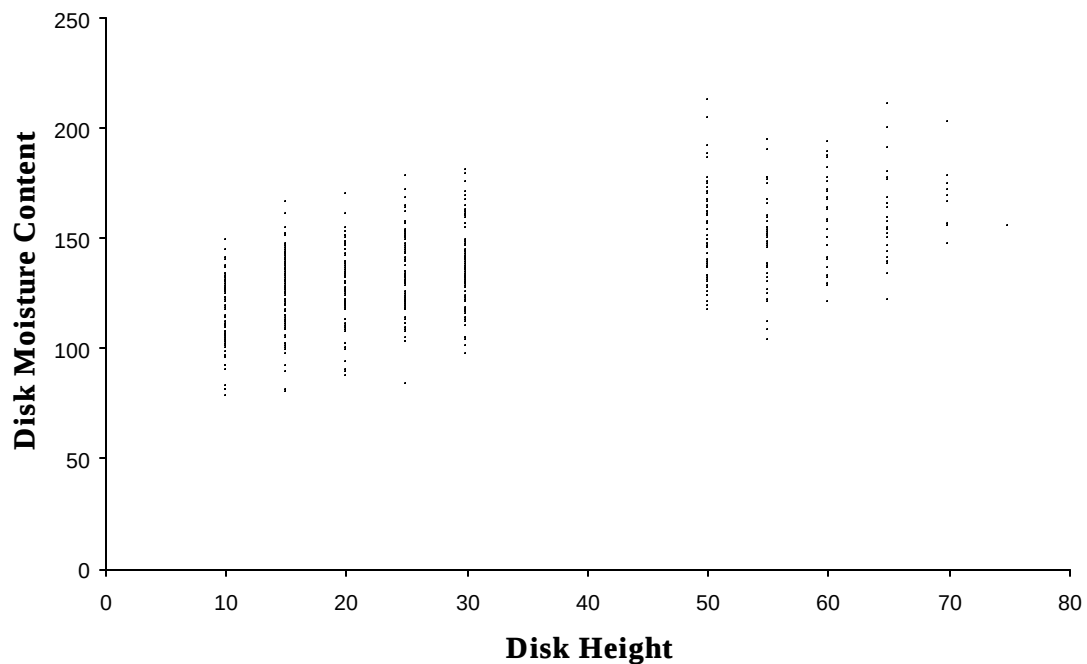


Figure 3.5. Moisture content increases with increasing disk height.

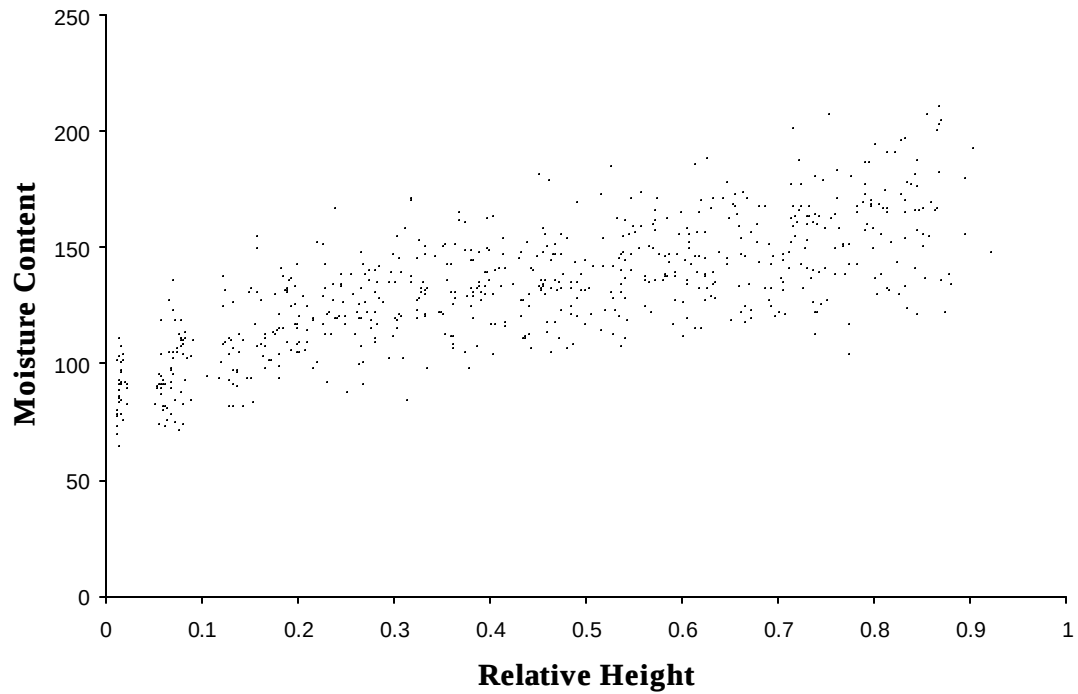


Figure 3.6. The relationship between moisture content and relative height is slightly curvilinear.

The Belehradek model (Ratkowsky 1990) seems appropriate for this curvilinear relationship.

$$Y = b_0(X - b_1)^{b_2}$$

The parameter b_0 has poor estimation properties, whereas b_1 and b_2 are close to linear (Ratkowsky 1990). So, b_0 was replaced by an expected value parameter, where y_1 is the expected-value parameter corresponding to $X=X_1$.

$$Y = y_1 [(X - b_1) / (X_1 - b_1)]^{b_2}$$

In this case,

$$MC_h = MC_D [(R_h - b_1) / (R_{ho} - b_1)]^{b_2} \quad (7)$$

where

MC_h = predicted moisture content at height h above ground ($0 \leq h \leq H$)

MC_D = moisture content at dbh.

This relationship also appears slightly linear. The simple linear model (8) was fit to the data, making each parameter tree specific, in order for comparison.

$$MC_h = b_0 + b_1 (R_h) \quad (8)$$

The Freundlich model (Ratkowsky 1990) also represents the trend of moisture content as a function of relative height because it can take on a linear form.

$$MC_h = b_0 + b_1(R_h)^{b_2}$$

As in model (5), this model was fit as a self-referencing function (9), modified by Ratkowsky (1990) to include an expected value parameter.

$$MC_h = MC_D + b_1 (R_h^{b_2} - R_{ho}^{b_2}) \quad (9)$$

Moisture Content = F (Diameter)

Prediction equations for moisture content as a function of diameter outside bark can be used to predict moisture content at any upper stem diameter. Moisture content decreases with increasing diameter outside bark (dob). Moisture content as a function of dob appears linear (Figure 3.7); however, graphs of the individual tree trend are somewhat curvilinear.

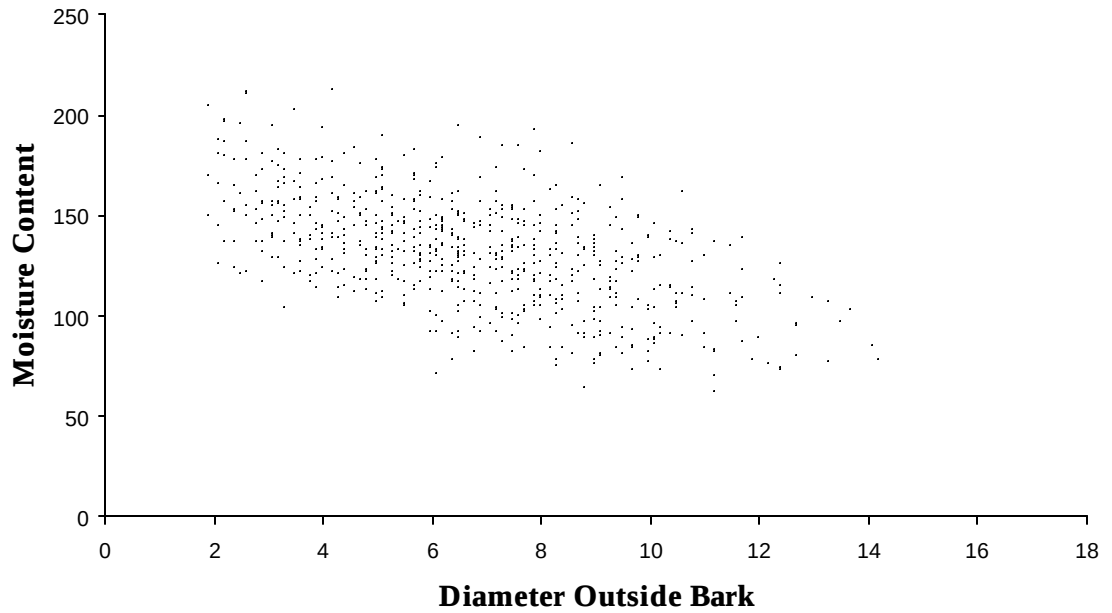


Figure 3.7. Moisture content as a function of dob appears linear.

Model forms similar to those used to describe moisture content as a function of height should work well for this relationship.

$$MC_h = b_0 + b_1 (dob) \quad (10)$$

$$MC_h = MC_D [(dob - b_1) / (D - b_1)]^{b_2} \quad (11)$$

$$MC_h = b_0 + b_1(dob)^{b_2} \quad (12)$$

These models may also be used along with the taper function, which predicts the stem profile, to predict MC_h along the stem profile.

“Best” Model Procedures

The “best” models, presented below in Chapter 4, were selected based on high R-square/Fit Index and low mean square error (MSE). In addition, the residual graphs were examined and required to have a random pattern. The actual versus predicted graphs were examined for patterns closest to linear.

The best models were tested for regional and site index differences, using the F-test based on the conditional error of full and reduced models (Neter *et al.* 1996). A full or unrestricted model was fit using SAS (PROC MODEL), nonlinear least squares (NLS). This full model included indicator variables for the lower coastal plain, site indices greater than or equal to 65 (base age 25), and the interaction. Prior work has identified similarities between the Upper Coastal Plain and Piedmont in this data set. The null hypotheses tested were:

1) H_{O1} : the parameters should be the same for all regions,

versus the alternative

H_{A1} : trees in the Lower Coastal Plain have specific gravity or moisture content curves that are significantly different from those in the other regions

2) H_{O2} : the parameters should be the same for both site classes,

versus the alternative

H_{A2}: the stands with site index greater than or equal to 65 have specific gravity or moisture content curves that are significantly different from those for the stands with site index less than 65 (base age 25).

3) H_{O3}: the parameters should be the same for all interactions, versus the alternative

H_{A3}: the interaction of site index and region is significant.

The full model, with all indicator variables, was compared to the reduced model, without indicator variables, to confirm improvement. A p-value ≤ 0.05 was used to verify significance of specific indicator variables. Non-significant indicator variables with p-value > 0.05 were eliminated, one at a time. From the full model, the parameter with the highest, non-significant p-value was eliminated, the model was refit with PROC MODEL, and compared to the reduced model again. If the model was “better,” then the parameter with the highest, non-significant p-value was eliminated, the model was refit with PROC MODEL, and so on. All parameters with p-values less than 0.05 were considered significant and utilized in the final model. This final model was compared to the reduced model to ensure improvement from the indicator variables.

It is assumed in regression that the independent variables are measured without error. However, this assumption is violated because it is known that the initial condition variable (SG_D or MC_D), in the self-referencing function, was measured with error. Specific gravity and moisture content at all sampling points are measured with error. In the past, this problem might have been

ignored and SG_D or MC_D would have been restricted to values equal to the observed data values. So, parts of the data known to contain stochastic elements, such as measurement or environmental errors, would be used as deterministic model parameters. These errors are important during parameter estimation; ignoring them causes erroneous identification of the process under study. It may cause curve shapes to be misidentified to an unknown degree (Cieszewski *et al.* 2000). In other words, using random variables on both sides of a regression equation is illogical, and may result in biased parameter estimates.

Cieszewski *et al.* (2000) note that, “The main problem with the traditional parameter estimation methods relates to the restrictive nature of the implicitly defined equations, which are required for the definition of the self-referencing models. In models based on such equations, the curves are forced through the exact values of the measurements’ errors whenever the models’ initial conditions assume values containing these errors.” Stochastic regression can be used to estimate model parameters simultaneously with the estimation of measurement errors in the initial conditions, correcting the traditional assumption that these initial conditions do not contain errors .

Bailey and Clutter (1974) introduced base-age invariance as a property of site-index curves, curves that are invariant under choices of base age. Invariant was defined as “unaffected by the group of mathematical operations under consideration.” Bailey and Cieszewski (2000) presented stochastic regression as a method for non-biased parameter estimation in self-referencing functions.

Stochastic regression was used in this project to account for the error on the right-hand side of the equation, in the independent variables SG_D and MC_D . Stochastic parameter estimation was used to produce global parameters for curves that are invariant under choices of disk height or diameter outside bark.

The model was fit designating the initial condition, SG_D or MC_D , as a random parameter, SG_x or MC_x . The stochastic parameter estimation technique allows the initial condition to vary with each individual tree, giving the best global parameters for the underlying trend. This technique fits the trend rather than forcing the curve through the observed value of SG_D or MC_D . Stochastic regression is explained in detail by Cieszewski *et al.* (2000).¹

¹ The code for this program is available on the Southern Mensurationists' web page at: <http://www.mensurationists.com/codes.htm>.

CHAPTER 4

RESULTS & DISCUSSION

Details for all candidate models are provided in this section. Four final models were selected as the “best” prediction models for specific gravity as a function of height, and as a function of diameter, moisture content as a function of height, and as a function of diameter.

Specific Gravity = F (Height)

Candidate prediction models for disk specific gravity as a function of height are shown in Table 4.1.

Table 4.1. Candidate models for $SG_h = f(H \text{ or } R_h)$.

Model	Specific Gravity = f (Height)	MSE	R-square
1	$SG_h = SG_D [(H - h) / (H - 4.5)]^{b_0}$	0.00106	0.5645
2	$SG_h = \log [1 - \{(R_h - b_0) / b_1\}^{(1/b_3)}] / b_2$	0.00760	0.5054
3	$SG_h = b_0 + b_1 [\log (R_h^{-b_2} - 1)]$	0.00115	0.5268

Many simple and advanced taper models were fit to the data. Model (1) has results representative of all the taper models attempted. The fit statistics are satisfactory; however, these models tend to be linear. They fail to describe the

nonlinear data points at the extremities of the tree. The fit statistics appear to be the most suitable, at this point, because model (1) has an initial condition, SG_D .

Various forms of the Chapman-Richards function were fit to the data. Model 2 has the best fit statistics and residual graphs of all Chapman-Richards variants. The Chapman-Richards-based models produced fairly linear predictions and had problems converging to stable solutions.

Many other nonlinear model types were fit based on the pattern of the actual data points. According to the fit statistics and residual graphs, Model 3 is the “best” model with specific gravity as a function of relative height. The worst-behaving parameter for this particular data was b_0 . The equation was transformed into a self-referencing function (3.1) by solving for b_0 , making it tree specific, and imposing the condition that $SG_h = SG_{h_0}$ when $h = h_0$. This expression for b_0 was substituted into the original equation (3), yielding a two-parameter function. Equation (3.1) is actually closer to linear than the original equation (Ratkowsky 1990).

$$b_0 = SG_{h_0} + b_1 [\log (R_{h_0}^{-b_2} - 1)]$$

$$SG_h = SG_D + b_1 \log[(R_h^{-b_2} - 1) / (R_{h_0}^{-b_2} - 1)] \quad (3.1)$$

Table 4.2. Fit statistics for the self-referencing $SG_h=f(R_h)$ reduced model (3.1).

MSE	R-square
0.000707	0.7085

Parameter estimates are provided in Table A1 (Appendix A).

Since it is the best model, Model 3.1 was tested for regional and site index differences using the F-test, based on the conditional error of full and reduced models (Neter *et al.* 1996). The hypotheses are stated in Methods, Chapter 3 (p.35). Parameter estimates and fit statistics for the full model are provided in Table A2, Appendix A. The first two null hypotheses (H_{01} and H_{02}) were rejected, so the model (3.2) has different parameter estimates for the Lower Coastal Plain and stands with site index greater than or equal to 65. The third null hypothesis (H_{03}) was not rejected, so the parameters should be the same for all interactions (LC*SI). The model became:

$$SG_h = SG_D + (b_{11} + b_{13} * SI) \times \log[(R_h^{-(b_{21} + b_{22} * LC + b_{23} * SI)} - 1) / (R_{ho}^{-(b_{21} + b_{22} * LC + b_{23} * SI)} - 1)] \quad (3.2).$$

Table 4.3. Fit statistics for the self-referencing $SG_h = f(R_h)$ model (3.2).

MSE	R-square
0.000618	0.7460

Parameter estimates are provided in Table A3 (Appendix A).

Next, stochastic parameter estimation was used defining SG_x as a random parameter for the initial condition. SG_x is defined as specific gravity at any reference height in the tree corresponding with R_{hx} = reference height (x) / total height. Since dbh is most popular for measurements, the most practical use may be $SG_x = SG_D$ and $R_{hx} = R_{ho}$. This model (3.3) is reference height invariant. For

example, the curve produced by choosing a reference height of 5 feet can be reproduced by selecting any other reference height.

$$SG_h = SG_x + (b_{11} + b_{13} * SI) \times \log[(R_h^{-(b_{21} + b_{22} * LC + b_{23} * SI)} - 1) / (R_{hx}^{-(b_{21} + b_{22} * LC + b_{23} * SI)} - 1)] \quad (3.3)$$

Table 4.4. Fit statistics from stochastic parameter estimation $SG_h = f(R_h)$ model (3.3).

MSE	R-square
0.000281	0.8951

Table 4.5. Parameter estimates for $SG_h = f(R_h)$, model (3.3), using stochastic parameter estimation.

Parameter	Estimate	Std Error	P-value
b11	0.031881	0.00187	<.0001
b13	-0.0122	0.00223	<.0001
b21	0.806918	0.1060	<.0001
b22	0.22405	0.0746	0.0027
b23	0.52018	0.1782	0.0036

Parameter estimates for each type of site are given here for application purposes.

$$SG_h = SG_x + b_1 \times \log[(R_h^{(-b_2)} - 1) / (R_{hx}^{(-b_2)} - 1)] \quad (3.4)$$

Table 4.6. Parameter estimates for $SG_h = f(R_h)$, by site condition, using model (3.4).

Site	b1	b2
Lower Coastal, SI ? 65	0.019681	1.551148
Upper Coastal/ Piedmont, SI ? 65	0.019681	1.327098
Lower Coastal, SI ? 65	0.031881	1.030968
Upper Coastal/ Piedmont, SI ? 65	0.031881	0.806918

Predicted $\widehat{SG}_h$ versus relative height (Figure 4.1) shows the same trend as the observed SG_h versus relative height (Figure 3.2). Stochastic parameter estimation (b) allows for more accuracy in this relationship (Figure 4.1). The observed SG_h versus the predicted $\widehat{SG}_h$ (Figure 4.2) shows the linear relationship between the observed and predicted values; stochastic regression improves this fit (d). All residual plots (Figures 4.3 and 4.4) improve with stochastic parameter estimation (d-f). There are no patterns in the residuals for this final model when plotted against observed SG_h , predicted $\widehat{SG}_h$, relative height, relative height at dbh, specific gravity at dbh, and age.

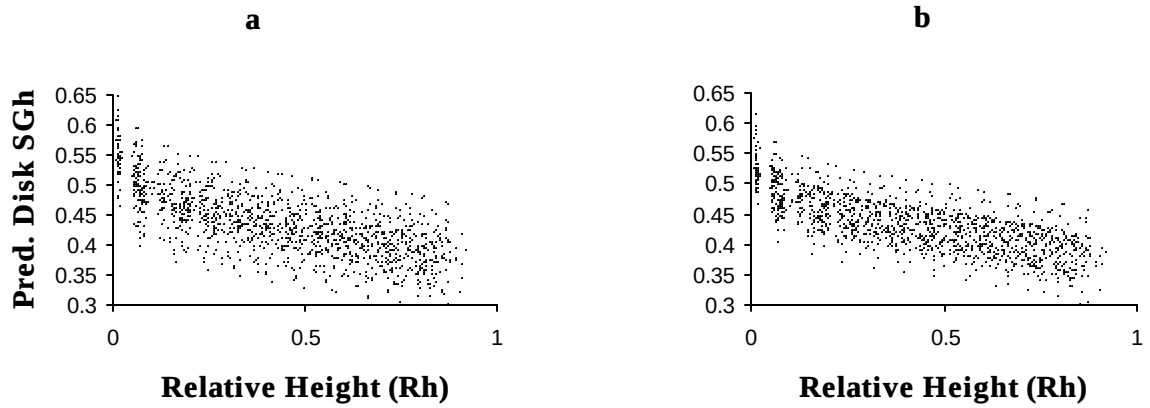


Figure 4.1. Observed SGh versus relative height (R_h) for specific gravity as a function of R_h , model (3), using NLS (a) and stochastic regression (b).

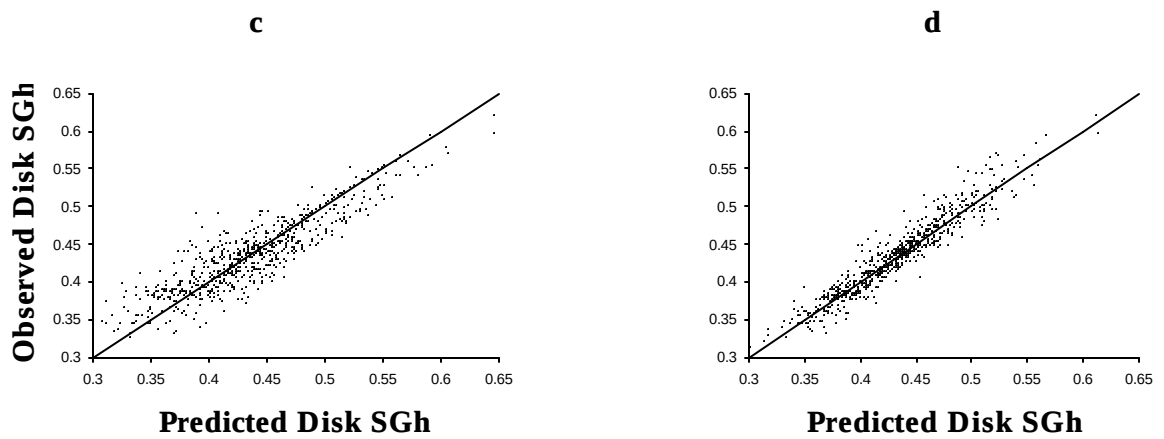


Figure 4.2. Observed specific gravity versus predicted disk specific gravity for specific gravity as a function of relative height, model (3), using NLS (c) and stochastic regression (d).

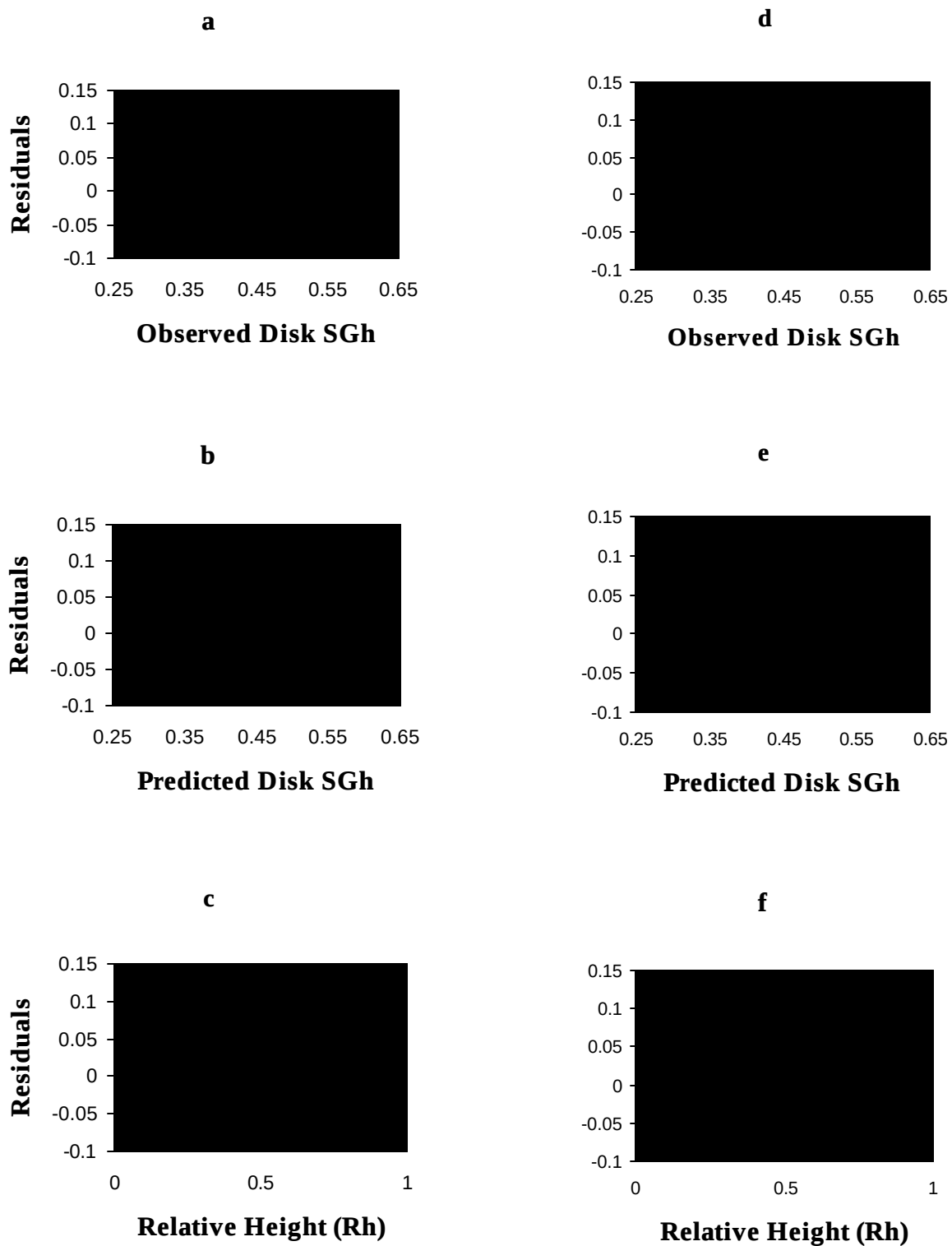


Figure 4.3. Residual plots for specific gravity as a function of relative height, model (3), using NLS (a-c) and stochastic regression (d-f).

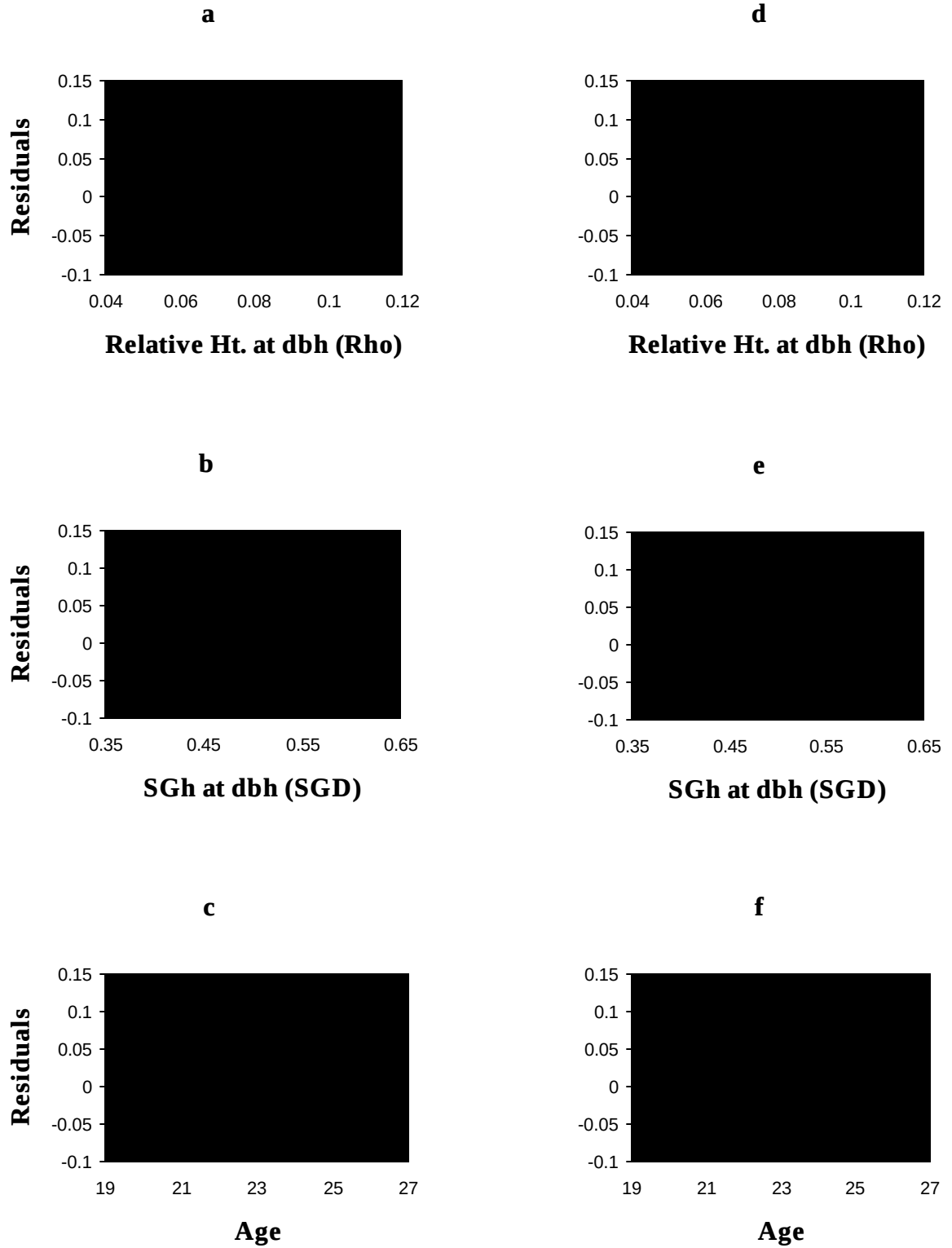


Figure 4.4. Residual plots for specific gravity as a function of relative height, model (3), using NLS (a-c) and stochastic regression (d-f).

If SG_x is unavailable, the original model (3) can be used along with the regional and site index parameters to predict this initial condition (3.5).

$$SG_x = b_0 + (b_{11} + b_{13} * SI) [\log (R_{hx}^{-(b_{21} + b_{22} * LC + b_{23} * SI)} - 1)] \quad (3.5)$$

All fit statistics and parameter estimates are the same, with $b_0 = 0.417019$. Note that b_0 is the tree specific parameter. The value of b_0 given here is the average of tree specific parameters from all of the trees in the database (Borders *et al.* 2001).

There was also an attempt to fit the model treating the indicator variable, SI, as a continuous variable. The fit statistics were not as good; however, the results are given here. Site index may have performed poorly as a continuous variable because the site data were collected as a classification variable, *i.e.* high or low. Site index was not designated as a continuous variable to represent the range of site indices across the state. The parameter b_{23} was not significant, in this case.

$$SG_h = SG_x + (b_{11} + b_{13} * SI) \times \log[(R_h^{-(b_{21} + b_{22} * LC)} - 1) / (R_{hx}^{-(b_{21} + b_{22} * LC)} - 1)] \quad (3.4)$$

Table 4.7. Fit statistics from stochastic parameter estimation $SG_h = f(R_h)$ with site index as a continuous variable, model (3.4).

MSE	R-square
0.000284	0.8939

Table 4.8. Parameter estimates for $SG_h = f(R_h)$, model (3.4), with site index as a continuous variable, using stochastic parameter estimation.

Parameter	Estimate	Std Error	P-value
b11	0.045653	0.003500	<.0001
b13	-0.000310	0.000044	<.0001
b21	0.982802	0.086300	<.0001
b22	0.411200	0.085900	<.0001

Specific Gravity = F (Diameter Outside Bark)

Candidate prediction models for disk specific gravity as a function of diameter outside bark (dob) follow (Table 4.9).

Table 4.9. Candidate models for $SG_h = f(dob)$.

Model	Specific Gravity = f (Height)	MSE	R-square
5	$SG_h = b_0 + b_1(dob)^{b_2}$	0.00161	0.3368
6	$SG_h = b_0 + b_1(dob)$	0.00161	0.3362

Parameter estimates are provided in Table A5 (Appendix A).

With the variety of curvilinear shapes throughout the data, Model (5) was considered because it takes on a wide range of curvilinear shapes. When b_0 is the worst-behaving parameter, it can be eliminated to yield,

$$SG_h = SG_D + b_1 (dob^{b_2} - dbh^{b_2}) \quad (5).$$

For the linear model,

$$SG_h = b_0 + b_1 (dob),$$

b1 had the greatest variance and became tree specific in the new self-referencing function (6), which was calculated by solving for b1.

$$SG_h = bo + [(SG_D - bo) / dbh] dob \quad (6)$$

Table 4.10. Candidate models for $SG_h = f(dob)$, redefined as self-referencing functions (reduced model).

Model	Specific Gravity = f (Height)	MSE	R-square
5	$SG_h = SG_D + b1 (dob^{b2} - dbh^{b2})$	0.001140	0.5316
6	$SG_h = bo + [(SG_D - bo) / dbh] dob$	0.000776	0.6798

Parameter estimates are provided in Table A6 (Appendix A).

Therefore, the nonlinear candidate model was not better than the linear model for specific gravity as a function of diameter.

F-tests for site class and region were conducted for the linear model with the same hypotheses as above, Chapter 3 (p. 35). Parameter estimates and fit statistics are provided for the full model in Table A7, Appendix A. The first two null hypotheses (H_{01} and H_{02}) were rejected, so the model (6.1) has different parameter estimates for the Lower Coastal Plain and stands with site index greater than or equal to 65. The third null hypothesis (H_{03}) was not rejected, so the parameters should be the same for all interactions (LC*SI). The model became:

$$SG_h = (bo1+bo2*LC+bo3*SI) + [(SG_D - (bo1+bo2*LC+bo3*SI)) / dbh] dob \quad (6.1).$$

Table 4.11. Fit statistics for the self-referencing $SG_h=f(dob)$ model (6.1).

MSE	R-square
0.000746	0.6928

Parameter estimates are provided in Table A8 (Appendix A).

Stochastic regression was used to estimate the parameters for the linear model with SG_D as a random parameter, SG_x (6.2). SG_x is defined as specific gravity at any reference dob in the tree corresponding with d = reference dob where SG_x is measured, and dob is defined at the desired prediction point.

$$SG_h = (bo1+bo2*LC+bo3*SI) + [(SG_x - (bo1+bo2*LC+bo3*SI)) / d] dob \quad (6.2)$$

Table 4.12. Fit statistics from stochastic parameter estimation $SG_h=f(dob)$ model (6.2).

MSE	R-square
0.000425	0.8411

Table 4.13. Parameter estimates for $SG_h = f(dob)$, model (6.2), using stochastic parameter estimation.

Parameter	Estimate	Std Error	P-value
bo1	0.304649	0.00312	<.0001
bo2	0.018316	0.00434	<.0001
bo3	0.024477	0.00442	<.0001

Parameter estimates for each type of site are given here for application purposes.

$$SG_h = bo + [(SG_x - bo) / d] dob \quad (6.3)$$

Table 4.14. Parameter estimates for $SG_h = f(dob)$, by site condition, using model (6.3).

Site	bo
Lower Coastal, SI ? 65	0.347442
Upper Coastal/ Piedmont, SI ? 65	0.329126
Lower Coastal, SI ? 65	0.322965
Upper Coastal/ Piedmont, SI ? 65	0.304649

The predicted $\hat{SG}_h$ versus dob (Figure 4.5) has nearly the same trend as the observed SG_h versus dob (Figure 3.3). The stochastic parameter estimation technique (b) allows for more accuracy in the relationship (Figure 4.5). The actual SG_h versus the predicted $\hat{SG}_h$ (Figure 4.6) shows the linear relationship between the observed and predicted values; stochastic regression improves this fit (d). There are no patterns in the residuals for this final model (Figure 4.7) when plotted against observed SG_h , predicted $\hat{SG}_h$, relative height, relative height at dbh, specific gravity at dbh, and age. Only residuals from stochastic parameter estimation are given, since the improvement has been illustrated.

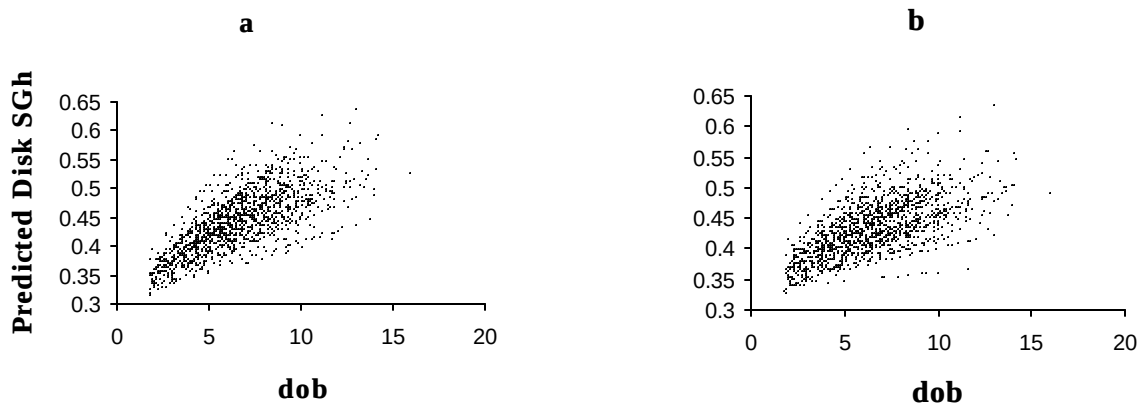


Figure 4.5. Predicted SGh versus diameter outside bark (dob) for specific gravity as a function of dob, model (6), using NLS (a) and stochastic regression (b).

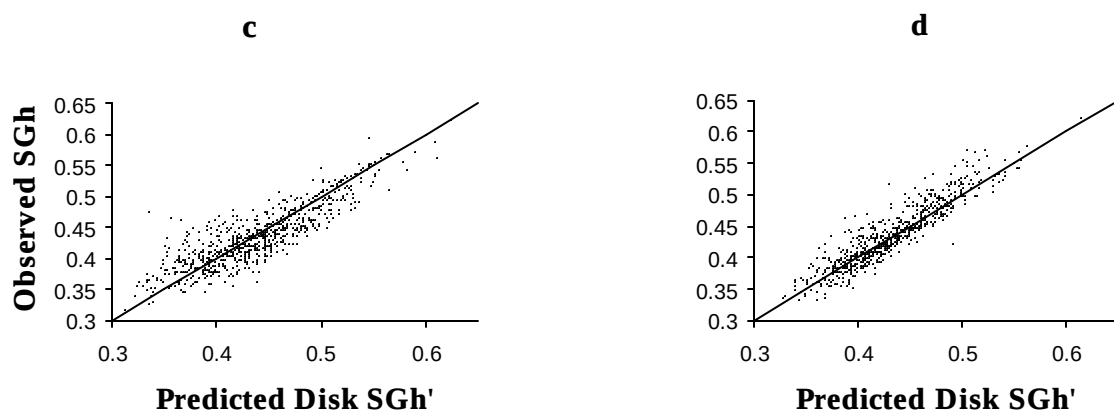


Figure 4.6. Observed specific gravity versus predicted specific gravity for specific gravity as a function of dob, model (6), using NLS (c) and stochastic regression (d).

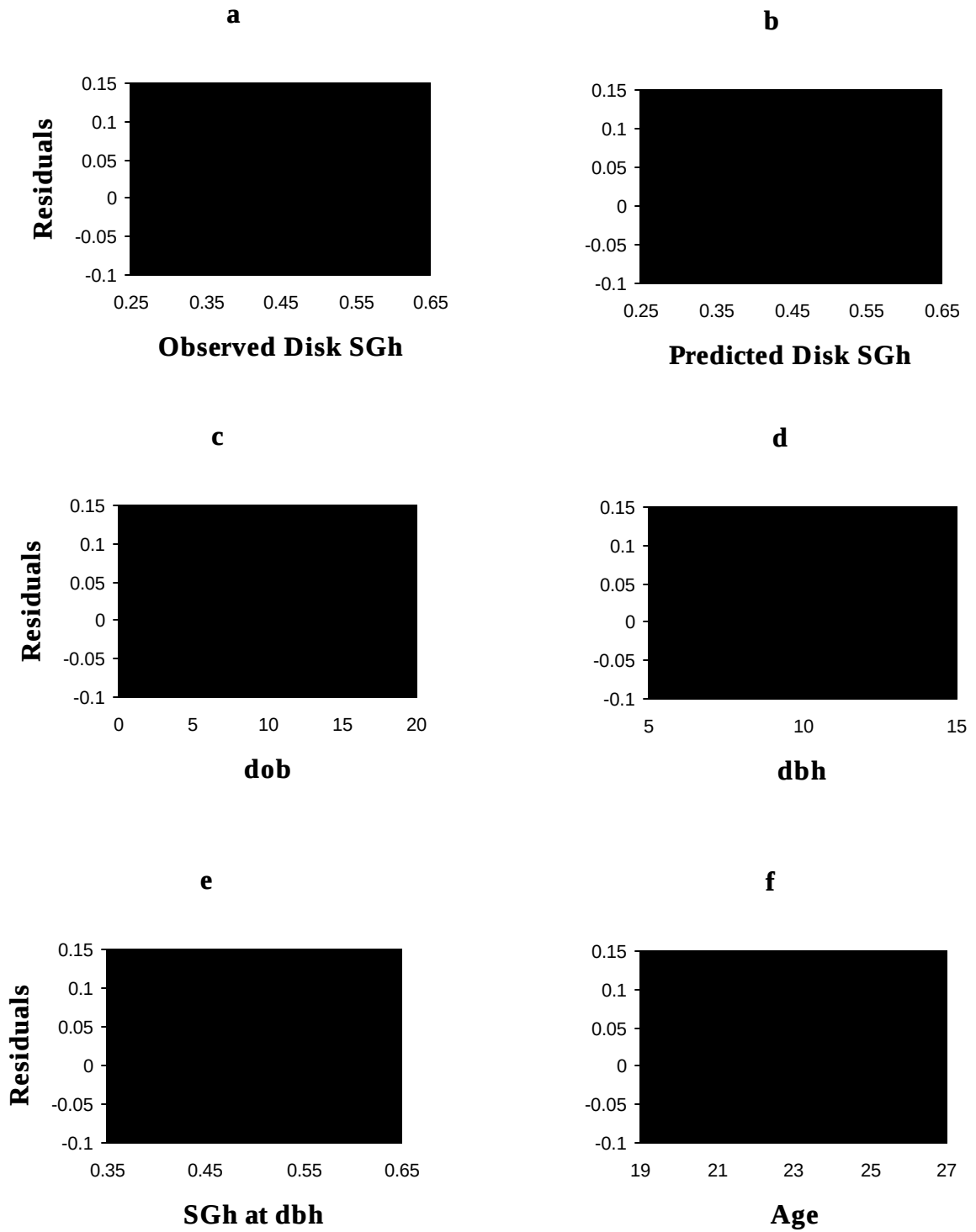


Figure 4.7. Residual plots for specific gravity as a function of dob, model (6), using stochastic regression.

If SG_x is unavailable, the original model (6) can be used along with the regional and site index parameters to predict this initial condition (6.4).

$$SG_h = (bo1+bo2*LC+bo3*SI) + b1 (dob) \quad (6.4)$$

All fit statistics and parameter estimates are the same, with $b1=0.017033$. Note that $b1$ is the tree specific parameter. The value of $b1$ given here is the average of tree specific parameters from all of the trees in the database (Borders *et al.* 2001).

Moisture Content = F (Height)

Candidate prediction models for disk moisture content as a function of relative height follow, Table 4.15.

Table 4.15. Candidate models for $MC_h = f(R_h)$.

Model	Specific Gravity = f (Height)	MSE	R-square
7	$MC_h = MC_D - b1R_{ho} + b1R_h$	0.0240	0.6674
8	$MC_h = MC_D [(R_h - b1) / (R_{ho} - b1)]^{b2}$	0.0237	0.6972
9	$MC_h = MC_D + b1(R_h^{b2} - R_{ho}^{b2})$	0.0197	0.7261

To compare the linear model (7) with the others, it was fit as a self-referencing function, making bo tree specific. This linear model did not describe the appropriate curve shape.

The Belehradek model (8) was improved compared to the linear model; however, it was unable to describe the curvilinear shape in the data. It produced linear predictions.

The Freundlich model (9) captures the relationship between moisture content and relative height. This model is reasonably close-to-linear, taking on several curve shapes depending on the parameters. It has the lowest MSE along with the highest R-square. The predicted curves look very similar to the actual curves. The parameter estimates for this reduced model (9) are provided in Table A9, Appendix A.

Since model (9) was selected as the “best” model, the F-test was used to test for significant regional and site index differences. The hypotheses are stated in Methods, Chapter 3 (p. 35). Parameter estimates and fit statistics for the full model are provided in Table A10, Appendix A. H_{02} was the only hypothesis rejected, so the model (9.1) requires different parameter estimates for stands with site index greater than or equal to 65 (base age 25). Using site index as a continuous variable for this model yields approximately equal R-square and MSE as the model with the site index indicator variable,

$$MC_h = MC_D + b_{11} (R_h^{b_{21}+b_{23}*SI} - R_{ho}^{b_{21}+b_{23}*SI}) \quad (9.1).$$

Table 4.16. Fit statistics for the self-referencing $MC_h=f(dob)$ model (9.1).

MSE	R-square
0.0191	0.7341

Parameter estimates are provided in Table A11 (Appendix A).

Stochastic regression was used to estimate the parameters for the linear model with MC_D as a random parameter, MC_x (9.2). MC_x is defined as moisture content at any reference height in the tree corresponding with R_{hx} = reference height (x) / total height.

$$MC_h = MC_x + b_{11} (R_h^{b_{21}+b_{23}*SI} - R_{hx}^{b_{21}+b_{23}*SI}) \quad (9.2)$$

Table 4.17. Fit statistics from stochastic parameter estimation $MC_h=f(R_{hx})$ model (9.2).

MSE	R-square
0.0097	0.8764

Table 4.18. Parameter estimates for $MC_h=f(R_{hx})$, model (9.2), using stochastic parameter estimation.

Parameter	Estimate	Std Error	P-value
b11	94.25341	2.1216	<.0001
b21	0.629893	0.0454	<.0001
b23	-0.190970	0.0413	<.0001

Parameter estimates for each type of site are given here for application purposes.

$$MC_h = MC_x + b_1(R_h^{b_2} - R_{hx}^{b_2}) \quad (9.3)$$

Table 4.19. Parameter estimates for $MC_h = f(R_h)$, by site condition, using model (9.3).

Site	b1	b2
Lower Coastal, SI ? 65	94.25341	0.438923
Upper Coastal/ Piedmont, SI ? 65	94.25341	0.438923
Lower Coastal, SI ? 65	94.25341	0.629893
Upper Coastal/ Piedmont, SI ? 65	94.25341	0.629893

The predicted $\widehat{MC}_h$ versus relative height (Figure 4.8) shows the same trend as the observed MC_h versus relative height (Figure 3.6). The stochastic parameter estimation (b) allows for more accuracy in this relationship (Figure 4.8). The observed MC_h versus the predicted $\widehat{MC}_h$ (Figure 4.9) shows the linear relationship between the observed and predicted values; stochastic regression improves this fit (d). There are no patterns in the residuals (Figure 4.10) for this final model when plotted against observed MC_h , predicted $\widehat{MC}_h$, relative height, relative height at dbh, specific gravity at dbh, and age.

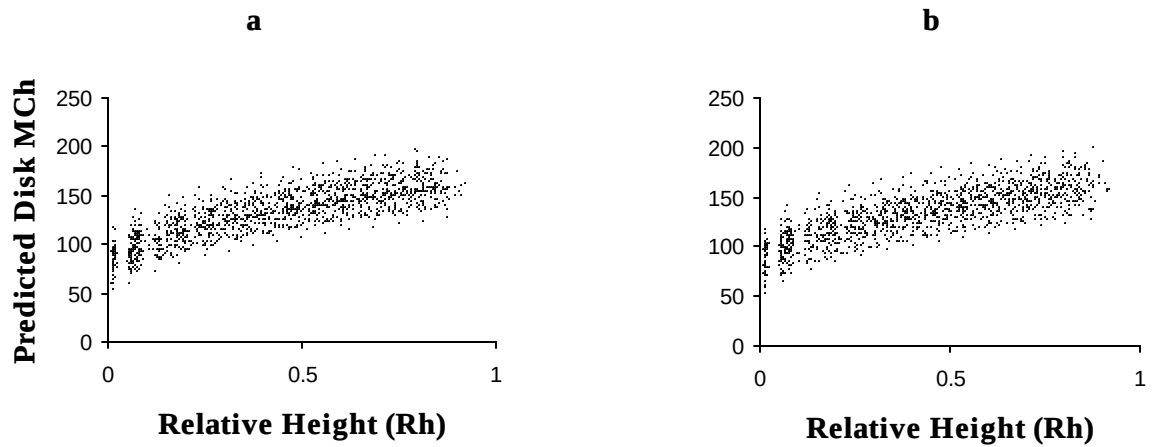


Figure 4.8. Predicted MCh versus relative height for moisture content as a function of relative height, model (9), using NLS (a) and stochastic regression (b).

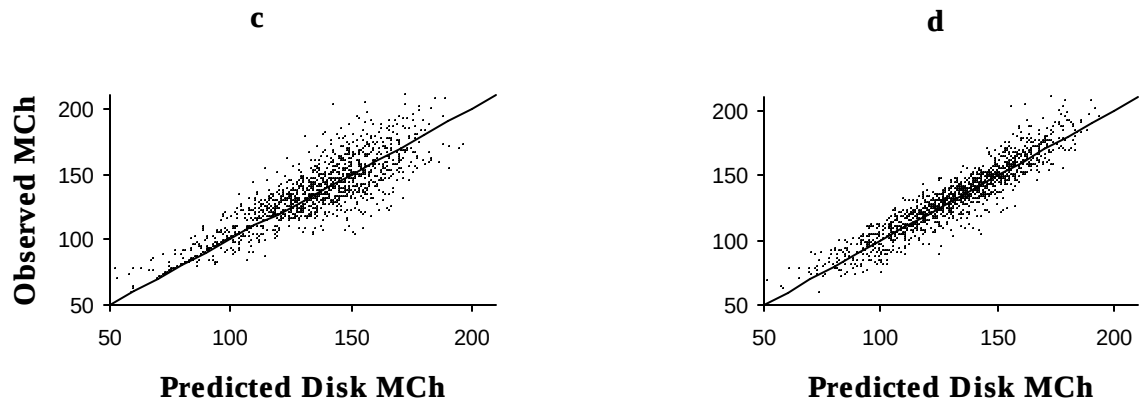


Figure 4.9. Observed moisture content versus predicted moisture content for moisture content as a function of relative height, model (9), using NLS (a) and stochastic regression (b).

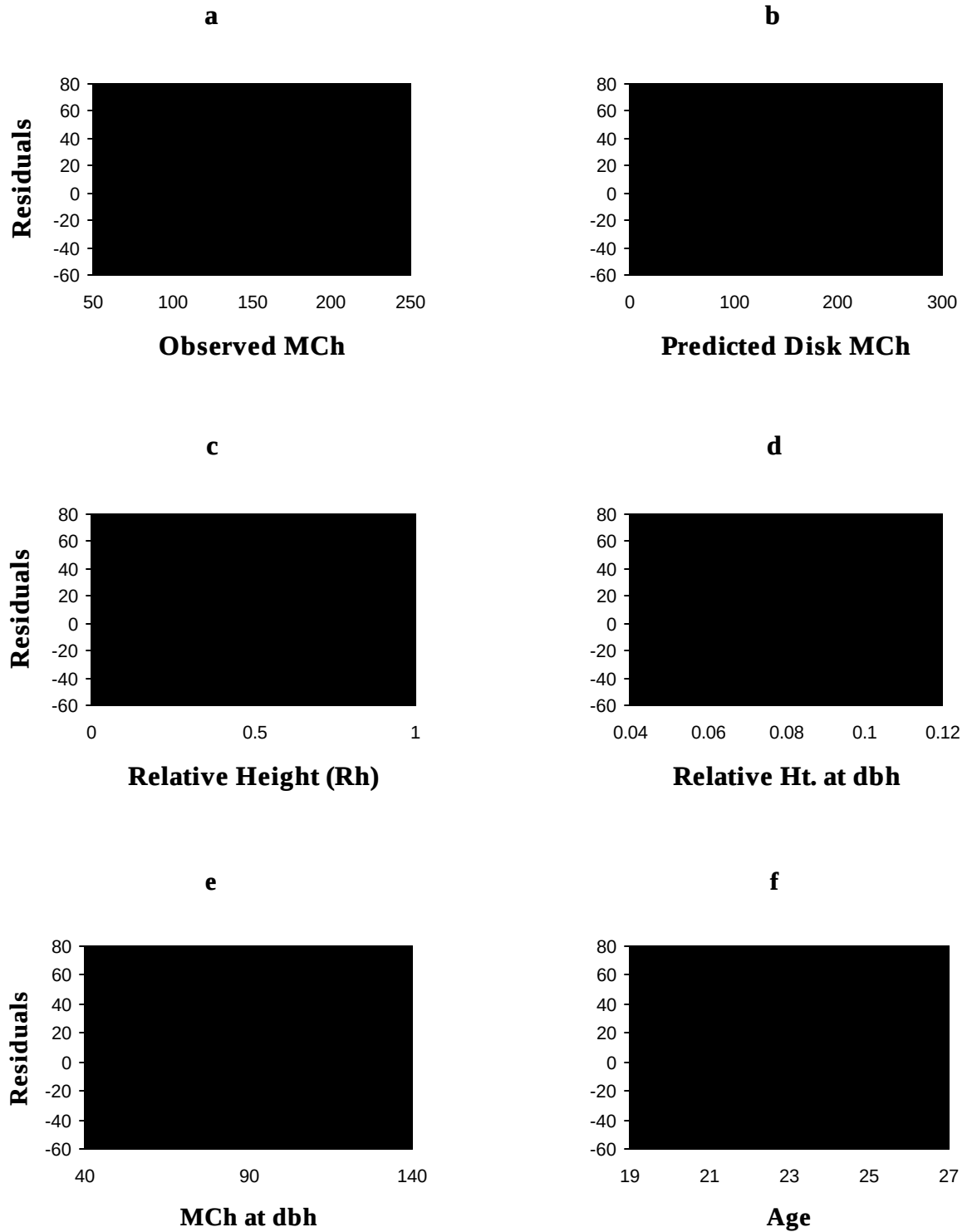


Figure 4.10. Residual plots for moisture content as a function of relative height, model (9), using stochastic regression.

If MC_x is unavailable, the original model (9) can be used along with the regional and site index parameters to predict this initial condition (9.4).

$$MC_x = b_0 + b_{11} (R_h)^{b_{21} + b_{23} * SI} \quad (9.4)$$

All fit statistics and parameter estimates are the same, with $b_0=74.14462$. Note that b_0 is the tree specific parameter. The value of b_0 given here is the average of tree specific parameters from all of the trees in the database (Borders *et al.* 2001).

Moisture Content = F (Diameter)

Candidate prediction models for disk moisture content as a function of diameter outside bark (dob) follow, Table 4.20. The models used for moisture content as a function of relative height should be appropriate. The relationships are very similar.

Table 4.20. Candidate models for $MC_h = f(dob)$.

Model	Specific Gravity = f (Height)	MSE	R-square
10	$MC_h = MC_D - b_1D + b_1dob$	0.0324	0.5492
11	$MC_h = MC_D [(dob - b_1) / (D - b_1)]^{b_2}$	0.0407	0.5104
12	$MC_h = MC_D + b_1(dob^{b_2} - D^{b_2})$	0.0318	0.5570

Moisture content as a function of diameter outside bark (dob) appears linear; however, graphs of the individual trees are somewhat curvilinear. The model search started with the simple linear model (10). This model describes a large amount of variation in moisture content. B_0 is tree-specific in this one-

parameter model. This model is one of the best prediction models for the relationship between moisture content and relative height.

The Belehradek model (11) modified by Ratkowsky (1990), produces linear results. Its fit statistics are worse than those for the linear model.

The Freundlich model (12) has somewhat better fit statistics than the linear model. It also seems to have a better fit to the data, with a more linear plot of observed versus predicted values of moisture content.

The F-test was used to test for regional and site index differences in model (12). The hypotheses are stated in Methods, Chapter 3 (p. 35). The parameter estimates for the reduced model above are in Table A12 (Appendix A), along with the fit statistics and parameter estimates for the full model in Table A13. The third hypothesis, H_{03} , was the only one not rejected. Hence, there is no need for different parameter estimates to adjust for the LC*SI interaction; however, the model (12.1) does require different parameter estimates for the Lower Coastal Plain (H_{01}) and site indices greater than 65 (H_{02}).

$$MC_h = MC_D + b_{11} (\text{dob}^{b_{21}+b_{22}*LC+b_{23}*SI} - \text{dbh}^{b_{21}+b_{22}*LC+b_{23}*SI}) \quad (12.1)$$

Table 4.21. Fit statistics for the self-referencing $MC_h=f(\text{dob})$ model (12.1).

MSE	R-square
0.0312	0.5658

Parameter estimates are provided in Table A14 (Appendix A).

Stochastic regression was used to estimate the parameters for the Freundlich model with MC_D as a random parameter, MC_x (12.2). MC_x is defined as moisture content at any reference height in the tree corresponding with d = reference dob where MC_x is measured, and dob is defined at the desired prediction point.

$$MC_h = MC_x + b_{11} (dob^{b_{21}+b_{22}*LC+b_{23}*SI} - d^{b_{21}+b_{22}*LC+b_{23}*SI}) \quad (12.2)$$

Table 4.22. Fit statistics from stochastic parameter estimation $MC_h=f(dob)$ model (12.2).

MSE	R-square
0.0137	0.8265

Table 4.23. Parameter estimates for $MC_h=f(dob)$, model (12.2), using stochastic parameter estimation.

Parameter	Estimate	Std Error	P-value
b11	-5.53118	0.9734	<.0001
b21	1.19112	0.0643	<.0001
b22	0.051815	0.0150	0.0006
b23	-0.06932	0.0148	<.0001

Parameter estimates for each type of site are given here for application purposes.

$$MC_h = MC_x + b_1(dob^{b_2} - d^{b_2}) \quad (12.3)$$

Table 4.24. Parameter estimates for $MC_h = f(\text{dob})$, by site condition, using model (12.3).

Site	b1	b2
Lower Coastal, SI ? 65	-5.53118	1.7361
Upper Coastal/ Piedmont, SI ? 65	-5.53118	1.1218
Lower Coastal, SI ? 65	-5.53118	1.2429
Upper Coastal/ Piedmont, SI ? 65	-5.53118	1.9112

The predicted $\widehat{MC}_h$ versus relative height (Figure 4.11) shows the same trend as the observed MC_h versus relative height (Figure 3.7). The stochastic parameter estimation (b) allows for more accuracy in this relationship (Figure 4.11). The observed MC_h versus the predicted $\widehat{MC}_h$ (Figure 4.12) shows the linear relationship between the observed and predicted values; stochastic regression improves this fit (d). There are no patterns in the residuals (Figure 4.13) for this final model when plotted against observed MC_h , predicted $\widehat{MC}_h$, relative height, relative height at dbh, specific gravity at dbh, and age.

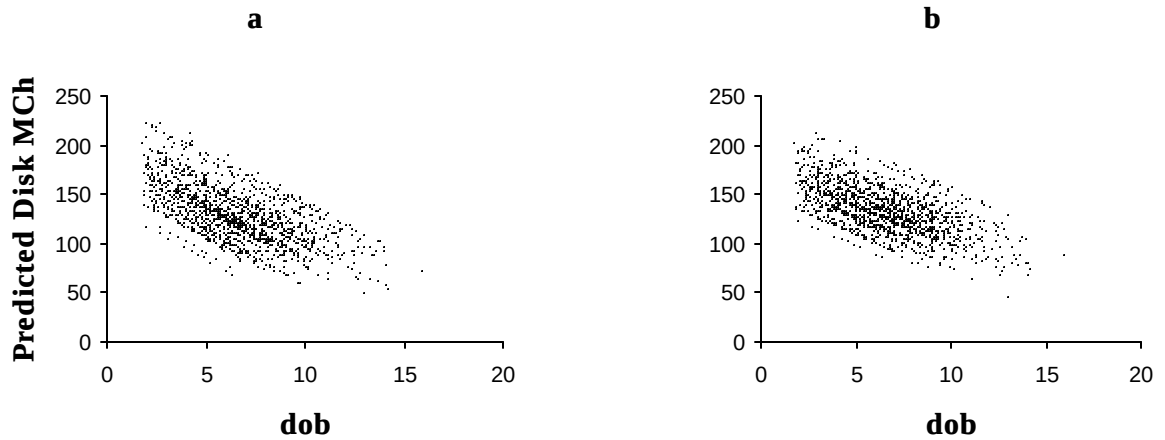


Figure 4.11. Predicted disk moisture content versus dob for moisture content as a function of dob, model (12), using NLS (a) and stochastic regression (b).

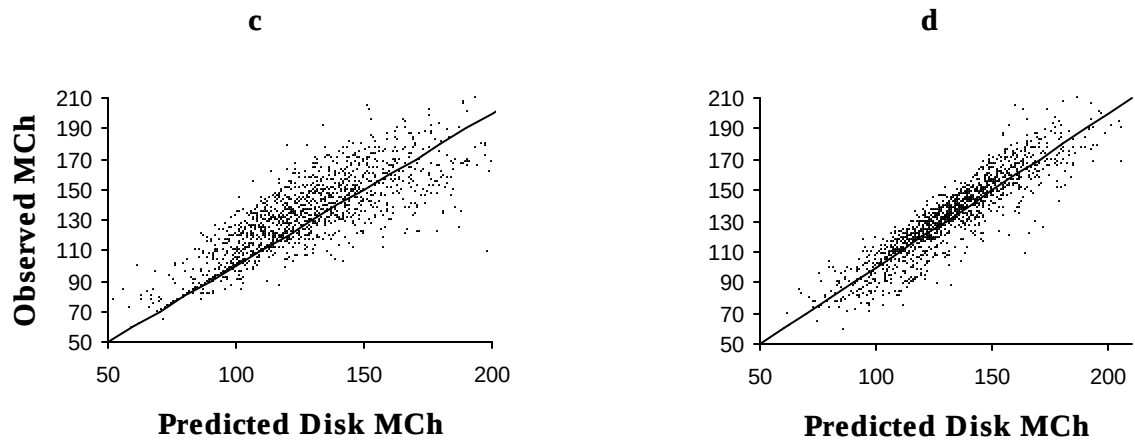


Figure 4.12. Observed disk moisture content versus predicted disk moisture content for moisture content as a function of dob, model (12), using NLS (c) and stochastic regression (d).

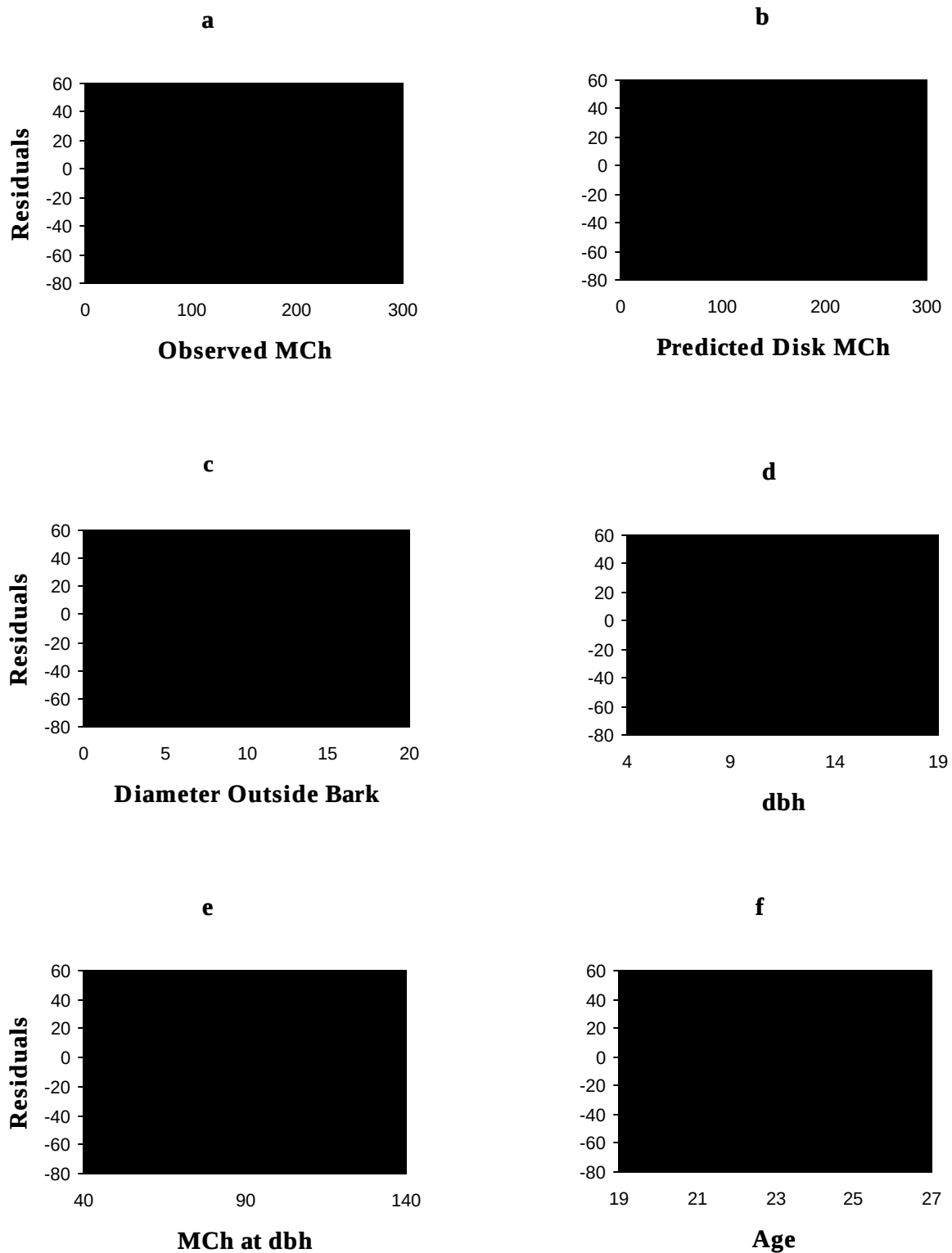


Figure 4.13. Residual plots for moisture content as a function of dob, model (12), using stochastic regression.

If MC_x is unavailable, the original model (9) can be used along with the regional and site index parameters to predict this initial condition (9.4).

$$MC_x = b_0 + b_{11} (dob)^{b_{21} + b_{22} * LC + b_{23} * SI} \quad (9.4)$$

All fit statistics and parameter estimates are the same, with $b_0=182.1391$. Note that b_0 is the tree specific parameter. The value of b_0 given here is the average of tree specific parameters from all of the trees in the database (Borders *et al.* 2001).

Model Discussion

Four final models were developed: 1) specific gravity as a function of relative height, 2) specific gravity as a function of diameter outside bark, 3) moisture content as a function of relative height, and 4) moisture content as a function of diameter outside bark. Relative height and diameter outside bark described the largest amount of variation and had the most predictable pattern with specific gravity and moisture content.

Regional and site index differences were detected with the Upper Coastal Plain and Piedmont having significantly different curves than those for the Lower Coastal Plain. The Upper Coastal Plain and Piedmont have lower disk specific gravity and greater disk moisture content averages compared to the Lower Coastal Plain (Table 4.25). The sites with site index less than 65 have greater disk specific gravity and lesser moisture content averages, for each region (Table 4.25). These differences were accounted for with indicator variables selected using the F-test.

Table 4.25. Average disk specific gravity and moisture content for each site condition in each region.

Wood Property	Lower C. Plain		Upper C. Plain		Piedmont	
	SI = 65	SI < 65	SI = 65	SI < 65	SI = 65	SI < 65
Disk SG	0.439	0.458	0.414	0.423	0.409	0.427
Disk MC	126.7	121.4	136.5	132.8	140.7	134.9

CHAPTER 5

CONCLUSIONS

The forest industry relies on loblolly pine as a primary wood source of raw material used in the construction of homes, decks and many engineered wood products such as plywood. There is a consistent demand for pine products and continued high rates of growth of pine plantations throughout the South. Intensive forest management practices are currently being implemented in loblolly pine plantations to meet market demands, encouraging short rotations on fast-growing plantations. These practices have increased the wood quantity, but the effect on quality is in question. There is a need to ensure the trees planted today can meet the demands of future consumers.

Prediction models were developed in this master's thesis for specific gravity and moisture content, two wood properties which are important measures of wood quality. Two prediction models for each wood property were presented, with dbh and height as independent variables. Stochastic regression was used to improve all models. These models have the ability to predict average disk specific gravity and moisture content along the stem profile. The equations with height as the predictor variable can be used along with an appropriate taper equation to predict weight to specific diameter limits. The

equations with diameter as the predictor variable allow prediction at any particular upper stem diameter.

Recommendations for future work include ring data analysis to provide for more detailed model description and prediction. Ring-by-ring data are now being collected. Earlywood and latewood are measured separately in the data, using an x-ray densitometer. These data will allow for the incorporation of changes by age from the pith into prediction equations. Ring-lead analysis will also help determine the separate effects of earlywood and latewood on wood properties. Then, it will be less difficult to determine the most appropriate uses for wood at varying ages or positions within the tree.

Another recommendation would be to extend this and future analysis south-wide to cover the full range of loblolly pine. Additional species, especially slash pine (*Pinus elliotti*), should also be examined.

Finally, equations of the type presented here should be incorporated into the taper-based volume prediction systems (Zhang *et al.* in press) to improve green and dry weight estimation.

CHAPTER 6

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APPENDIX A

PARAMETER ESTIMATES & FIT STATISTICS

SG_h = F (Relative Height)

Table A1. Parameter estimates for the self-referencing SG_h=f(R_h) reduced model (3.1).

$$SG_h = SG_D + b_1 \log[(R_h^{-b_2}-1) / (R_{h0}^{-b_2}-1)]$$

Parameter	Estimate	Std Error	P-value
b1	0.02617	0.00157	<.0001
b2	1.243972	0.1231	<.0001

Table A2. Parameter estimates and fit statistics for the self-referencing SG_h=f(R_h) full model.

$$SG_h = SG_D + (b_{11} + b_{12}*LC + b_{13}*SI + b_{14}*LC*SI) \times \log[(R_h^{-(b_{21}+b_{22}*LC+b_{23}*SI+b_{24}*LC*SI)} - 1) / (R_{hx}^{-(b_{21}+b_{22}*LC+b_{23}*SI+b_{24}*LC*SI)} - 1)]$$

Parameter	Estimate	Std Error	P-value
b11	0.041292	0.00269	<.0001
b12	-0.01892	0.0134	0.1585
b13	-0.02039	0.00383	<.0001
b14	0.013934	0.0139	0.3167
b21	0.670694	0.1185	<.0001
b22	1.138996	1.4685	0.4381
b23	0.71953	0.3010	0.0170
b24	-0.086078	1.5615	0.9560

MSE	R-square
0.000610	0.7499

Table A3. Parameter estimates for $SG_h = f(R_h)$, model (3.2).

$$SG_h = SG_D + (b_{11} + b_{13} * SI) \times \log[(R_h^{-(b_{21} + b_{22} * LC + b_{23} * SI)} - 1) / (R_{ho}^{-(b_{21} + b_{22} * LC + b_{23} * SI)} - 1)]$$

Parameter	Estimate	Std Error	P-value
b11	0.039324	0.00262	<.0001
b13	-0.02018	0.00316	<.0001
b21	0.731795	0.1233	<.0001
b22	0.27087	0.0500	<.0001
b23	0.90733	0.2507	0.0003

Table A4. Parameter estimates for $SG_h = f(R_h)$, model (3.3), with site index as a continuous variable.

$$SG_h = SG_x + (b_{11} + b_{13} * SI) \times \log[(R_h^{-(b_{21} + b_{22} * LC + b_{23} * SI)} - 1) / (R_{ho}^{-(b_{21} + b_{22} * LC + b_{23} * SI)} - 1)]$$

Parameter	Estimate	Std Error	P-value
b11	0.045653	0.00350	<.0001
b13	-0.00031	0.000044	<.0001
b21	0.982802	0.0863	<.0001
b22	0.4112	0.0859	<.0001

*b23 was non-significant for this fit.

SG_h = F (Diameter Outside Bark)

Table A5. Parameter estimates for SG_h = f (dob), initial model (5 and 6).

$$SG_h = b_0 + b_1(dob)^{b_2} \quad (5)$$

Parameter	Estimate	Std Error	P-value
b₀	0.345273	0.0160	<.0001
b₁	0.018857	0.00906	0.0376
b₂	0.82286	0.1556	<.0001

$$SG_h = b_0 + b_1 (dob) \quad (6)$$

Parameter	Estimate	Std Error	P-value
b₀	0.360019	0.00300	<.0001
b₁	0.011114	0.000425	<.0001

Table A6. Parameter estimates for SG_h = f (dob), model (5 and 6), redefined as self-referencing functions (reduced model).

$$SG_h = SG_D + b_1 (dob^{b_2} - dbh^{b_2}) \quad (5)$$

Parameter	Estimate	Std Error	P-value
b₁	0.025999	0.00437	<.0001
b₂	0.911062	0.0551	<.0001

$$SG_h = b_0 + [(SG_D - b_0) / dbh] dob \quad (6)$$

Parameter	Estimate	Std Error	P-value
b₀	0.30459	0.00199	<.0001

Table A7. Parameter estimates and fit statistics for the self-referencing $SG_h=f(dob)$ full model (6).

$$SG_h = (bo1+bo2*LC+bo3*SI+bo4*LC*SI) + [(SG_D - bo1+bo2*LC+bo3*SI+bo4*LC*SI)) / dbh] dob$$

Parameter	Estimate	Std Error	P-value
bo1	0.281893	0.00363	<.0001
bo2	0.027546	0.0149	0.0638
bo3	0.027123	0.00509	<.0001
bo4	-0.01894	0.0156	0.2245

MSE	R-square
0.000746	0.6931

Table A8. Parameter estimates and fit statistics for the self-referencing $SG_h=f(dob)$ model (6.1).

$$SG_h = (bo1+bo2*LC+bo3*SI) + [(SG_D - bo1+bo2*LC+bo3*SI)) / dbh] dob$$

Parameter	Estimate	Std Error	P-value
bo1	0.282918	0.00353	<.0001
bo2	0.010351	0.00451	0.0218
bo3	0.025105	0.00481	<.0001

MC_h = F (Relative Height)

Table A9. Parameter estimates for the self-referencing MC_h=f(R_h) reduced model (9).

$$MC_h = MC_D + b_1(R_h^{b_2} - R_{ho}^{b_2})$$

Parameter	Estimate	Std Error	P-value
b1	107.2069	3.3271	<.0001
b2	0.429864	0.0334	<.0001

Table A10. Parameter estimates and fit statistics for the self-referencing MC_h=f(R_h) full model.

$$MC_h = MC_D + (b_{11} + b_{12} * LC + b_{13} * SI + b_{14} * LC * SI)(R_h^{b_{21} + b_{22} * LC + b_{23} * SI + b_{24} * LC * SI} - R_{ho}^{b_{21} + b_{22} * LC + b_{23} * SI + b_{24} * LC * SI})$$

Parameter	Estimate	Std Error	P-value
b11	105.6882	3.1620	<.0001
b12	67.93163	218.8	0.7562
b13	11.02354	12.3642	0.3728
b14	-66.7765	219.3	0.7608
b21	0.574731	0.0591	<.0001
b22	-0.37988	0.3460	0.2725
b23	-0.25768	0.0851	0.0025
b24	0.39766	0.3556	0.2637

MSE	R-square
0.0191	0.7357

Table A11. Parameter estimates for the self-referencing $MC_h=f(R_h)$ model (9.1).

$$MC_h = MC_D + b_{11} (R_h^{b_{21}+b_{23}*SI} - R_{ho}^{b_{21}+b_{23}*SI})$$

Parameter	Estimate	Std Error	P-value
b11	109.5533	3.3021	<.0001
b21	0.509828	0.0464	<.0001
b23	-0.1336	0.0291	<.0001

 $MC_h = F$ (Diameter Outside Bark)**Table A12. Parameter estimates for the self-referencing $MC_h=f(dob)$ reduced model (12).**

$$MC_h = MC_D + b_1(dob^{b_2} - D^{b_2})$$

Parameter	Estimate	Std Error	P-value
b1	-10.6864	1.6651	<.0001
b2	1.014442	0.0527	<.0001

Table A13. Parameter estimates and fit statistics for the self-referencing $MC_h=f(dob)$ full model.

$$MC_h = MC_D + (b_{11}+b_{12}*LC+b_{13}*SI+b_{14}*LC*SI) (dob^{b_{21}+b_{22}*LC+b_{23}*SI+b_{24}*LC*SI} - D^{b_{21}+b_{22}*LC+b_{23}*SI+b_{24}*LC*SI})$$

Parameter	Estimate	Std Error	P-value
b11	-31.8084	9.4112	0.0007
b12	0.239626	0.6120	0.6955
b13	26.11251	9.5833	0.0065
b21	0.678758	0.0887	<.0001
b22	0.054884	0.0365	0.1325
b23	0.522292	0.1172	<.0001

*This model would not converge to a stable solution with b14 and b24 included.

MSE	R-square
0.0306	0.5762

Table A14. Parameter estimates for the self-referencing $MC_h=f(dob)$ model (12.1).

$$MC_h = MC_D + b_{11} (dob^{b_{21}+b_{22}*LC+b_{23}*SI} - D^{b_{21}+b_{22}*LC+b_{23}*SI})$$

Parameter	Estimate	Std Error	P-value
b11	-10.0808	1.5729	<.0001
b21	1.052136	0.0547	<.0001
b22	0.039909	0.00939	<.0001
b23	-0.04784	0.0104	<.0001