academicJournals

Vol. 8(22), pp. 2685-2695, 13 June, 2013
DOI: 10.5897/AJAR2013.6920
ISSN 1991-637X ©2013 Academic Journals
http://www.academicjournals.org/AJAR

African Journal of Agricultural Research

Full Length Research Paper

Path models-approach to the study of the effect of climatic factors and tree age on radial growth of juvenile *Eucalyptus* hybrid clones

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Accepted 30 May, 2013

Due to increasing wood consumption and pulp and paper demands, plantations of fast growing tree species, have a growing importance for the sustainability of industrial wood raw material. Consequently, the efficient utilization of fast growing plantations can have a large impact on productivity. Adequate management requires good understanding of factors affecting tree growth. This study aimed to determine the factors that influence stem radial growth of juvenile *Eucalyptus* hybrids grown in the east coast of South Africa. Measurement of stem radius was conducted using dendrometers on sampled trees of two *Eucalyptus* hybrid clones (*Eucalyptus grandis* × *Eucalyptus urophylla*, GU and *E. grandis* × *Eucalyptus camaldulensis*, GC). Daily averages of climatic data (temperature, solar radiation, relative humidity and wind speed) were simultaneously collected with total rainfall from the site. In this study, path analysis was employed. The joint effect of the climatic variables as well as the direct effect of each climatic variable was studied. Bootstrap estimation procedures, which relax the distributional assumption of the maximum likelihood estimation method, were used. It is found that all variables had a positive effect on stem radial growth. The study showed that tree age is the most important determinant of radial measure.

Key words: Bootstrap, cross-validation, dendrometer, maximum likelihood, path analysis, standardized regression weights.

INTRODUCTION

Eucalyptus has increasingly become the most widely planted, hardwood genus in the world (Turnbull, 1999). Eucalypts provide sawn timber, mine props, paper, pulp, fiberboard, poles, firewood, charcoal, essential oils, honey and tannin products. Eucalypt plantation growth rate is an important economic factor as fast growing trees will be available for processing earlier compared to slower growing trees. Tree growth and the ultimate production of wood is a product of the interaction of genetic (Kozlowski and Pallardy, 1997; Apiolaza et al., 2005; Zweifel et al., 2006), silvicultural (Pallett and Sale, 2004) and environmental factors (Gallaham, 1962; February et al., 1995; Searson et al., 2004; Drew and Pammenter, 2006).

Climatic factors such as temperature, humidity, sunlight, rainfall (Eagleman, 1985; Miller, 2001) and wind speed (Wadsworth, 1959) contribute to the growth of plants. Growth generally occurs under a broad range of climatic variables, but ideal growth occurs during optimum climatic conditions. The net contribution of each climatic variable is, however, often masked or influenced by one or more other climatic variables. Understanding

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the relationships between climatic variables and the pattern of stem growth would facilitate the prediction of wood properties for a given site. However, such studies are limited. Available studies commonly focus on growth rate and pattern of growth as a function of age (Miehle et al., 2009; Crecente-Campo et al., 2010; Mateus and Tomé, 2011). Downes et al. (1999) studied the effects of climatic variation on radial growth of irrigated eucalypts in Australia. The work of Downes et al. (1999) focused on daily stem growth patterns in irrigated *Eucalyptus globulus* and *E. nitens* in relation to climate. Applying multiple regressions, they have shown that weather variables accounted for 40 to 50% of the variance in stem radial increment. Downes et al. (2009) gave an excellent overview on measuring and modeling stem growth and wood formation. Since most eucalypt plantations rely on natural conditions for growth (no irrigation), assessments of the effects of the natural environment is useful to begin to understand what the potential impact of drought or even climate change may have, not only on growth, but potentially also on wood properties. Drew et al. (2009) studied the relationship between stem radius and climatic factors using the correlation matrix. The methods used by both Downes et al. (1999) and Drew et al. (2009) do not permit any other relationships among the independent variables to be specified. This limits the potential of the variables to have direct, indirect and total effects on each other. The path models approach used in this study can overcome these limitations. This paper describes the effects of tree age and climatic variation on radial growth of *Eucalyptus grandis* × *E. urophylla* (GU) and *E. grandis* × *E. camaldulensis* (GC) hybrid clones established in Zululand on the eastern coast of South Africa. The particular emphasis of this paper is on determining the climatic factors that most influence radial growth of *Eucalyptus* hybrid clones during the juvenile stages of growth.

MATERIALS AND METHODS

Study design

A dendrometer trial, which focused on the growth of two *Eucalyptus* hybrid clones was established on Sappi landholdings at KwaMbonambi (28.53° S, 32.140 E, 55 m MASL) on the Zululand coast in the eastern part of South Africa. On average, the site receives 1,000 mm of rainfall per annum and has a mean annual temperature of 21°C (Drew et al., 2009). The experiment was designed to extend over a seven-year period divided into separate phases of growth. Each phase ended with the destructive sampling of study trees to facilitate measurement of wood anatomical characteristics. The results presented in this study are based on the data collected only during the first of these phases of growth. This phase ran for 16 months from April 2002 until August 2003. Two *Eucalyptus* hybrid clones, *E. grandis* × *E. urophylla* (GU) and *E. grandis* × *E. camaldulensis* (GC), which were commercially deployed at the time, were established in the trial (Drew, 2004).

Planting took place on 16 July 2001. Prior to planting, in April 2001, stumps of the trees from the previous rotation on the site were treated with herbicide (to prevent coppicing) and slash from harvest was burnt. Each rooted cutting was planted in a planting pit between existing stumps, with approximately two liters of water. The two clones were planted in alternating blocks (three repeats) of 7 × 24 trees at a spacing of 3 m (E-W) × 2.5 m (N-S). Within each block of a particular clone, three plots of 12 (3×4) trees, each with two surrounding rows of trees were identified. The plots were established as pairs, such that for any phase of the research, a GU and a GC plot could be measured simultaneously. Within a 12 tree plot, nine trees were selected from each clone for intensive monitoring of radial growth and other physiological characteristics during Phase 1 (Drew, 2004). Radial growth (μm) was measured using 18 electric point dendrometers (AEC) mounted on nine trees per clone in adjacent plots. One dendrometer was mounted on the north side of each sampled tree, at breast height (1.3 m), from when trees were nine-months-old. In addition to radial growth, an automatic weather station was installed at a distance of approximately 200 m from the trial to record hourly temperature (°C), relative humidity (%), solar radiation (mJ/h), rainfall (mm) and wind speed (m/s). Later on the daily total rainfall and the daily average of other variables were obtained from the hourly data. The data set used in this study has a total of 8,640 observations for the two clones which is the daily data. Half the data set pertains to the GU clone and the remaining half to the GC clone.

Data analysis

The statistical method employed to analyze the data is path analysis. A brief description of path analysis and its relation to the classical regression model is given. Path analysis is the statistical technique used to examine causal relationships between two or more variables. It involves a set of simultaneous regression equations that theoretically establish the relationship among observed variables in the path model. Path analysis extends the idea of regression modeling and gives the flexibility of quantifying indirect and total causal effects in addition to the direct effect which is also possible in regression analysis (Bollen, 1989). In other words, regression analysis allows an independent variable to influence an outcome variable only directly. Path analysis however gives more flexibility and predictor variables are allowed to influence the outcome variable directly as well as indirectly through other mediating variables. Path analysis shares the following principles of regression analysis:

1. The direction of influence in the relationship of variables should be specified from the theory behind the investigation;
2. Independent variables are assumed to be measured without error.
3. The relationship between target variables is linear.
4. Any outcome variable in the system of equations under investigation has an error term attached to it.

Path analysis is an extension of the regression model, which researchers use to test the fit of a correlation matrix with a causal model that has been, tested (Garson, 2004). The aim of path analysis is to provide estimates of the magnitude and significance of the hypothesized causal connections among sets of variables displayed through the use of path diagrams. There are three interrelated components in path analysis (Bollen, 1989):

1. The translation of a conceptual problem into pictorial presentation, which shows the network of relationships;
2. Obtaining systems of equations that relate observed correlation and covariance to parameters; and
3. Decomposition of effects of one variable on another (that is, direct, indirect and total effects) from the correlation of measured variables.

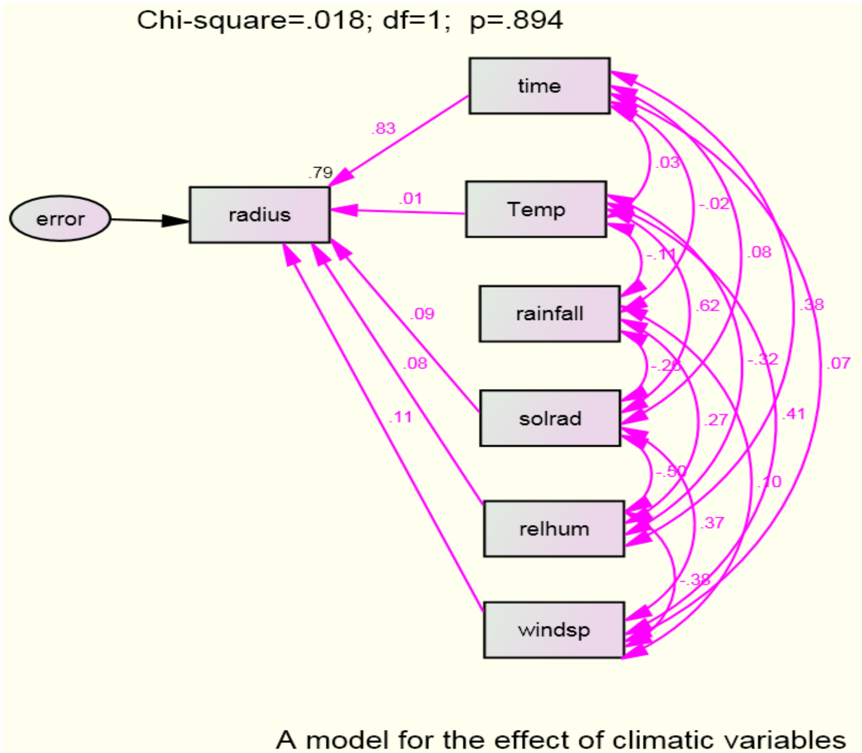

Figure 1. Path diagram showing the effect of age and climatic variables on radius of *Eucalyptus* hybrid clones during the first measured phase of growth. Time = age; solrad = solar radiation; relhum = relative humidity; windsp = wind speed.

The statistical analyses were performed using AMOS software (Amos Development Corporation). Path analysis was conducted by considering the radial measure as dependent climatic variables and age as independent factors explaining the radial growth. The chi-square statistic, the normed fit index (NFI), and root mean square error of approximation (RMSEA) were used to estimate model fit. The larger the probability associated with the chi-square, the better the fit of the model to the data (Bollen, 1989; Byrne, 2001). The NFI tests the hypothesized model against a reasonable baseline model and ideally should be 1·0. A RMSEA of < 0·10 is considered a good fit and < 0·05 is very good and lower than 0.01 is considered as beautiful fit (Steiger, 1990). Model validity was assessed using the expected cross validation index (ECVI). Path significance was based on the critical ratio (CR), with a CR > 2 in absolute value considered as significant (Arbuckle, 2006; Schumacker and Lomax, 2004).

RESULTS AND DISCUSSION

The independent variables included in the study were the five major climatic variables that were measured and the age of the trees. The association between the independent variables and the radial growth measurement of the clones is presented in Figure 1. The numbers displayed at the top of the diagram refer to the goodness of fit of the model. This fit statistic is the likelihood ratio chi-square test. The p-value associated with this measure is 0.894, which is by far larger than 0.05 and indicates a non-statistical significance of the chi-square test. This implies the model is consistent with the data. The numbers displayed next to the double headed arrows are estimated correlation coefficients.

Various measures of fit (Table 1) are presented for the fitted model, given in Figure 1, and include the saturated model, which is the ideal fit by including all possible paths. A model that can be defined as good is one that does not differ significantly from the saturated model despite omitting paths from the saturated model. On the other hand, the ordinary regression model or independent model fits by ignoring any potential relatedness between the independent variables thus considering all correlations among the independent variables as zero.

The statistical significance of individual parameter estimates for the paths in the fitted model (Figure 1) is one of the important criteria to be studied. The significance can be seen by computing the critical values, which are obtained by dividing the parameter estimates by their respective standard errors. The computed critical values together with the corresponding p-values are presented in Table 2. The regression weights for all variables were significant with the exception of rainfall, which was dropped from the model.

The other issue to consider at this stage is the magnitude and direction of the parameter estimates. In this particular model all the regression weights were

Table 1. Different fit measures for the fitted model, saturated and ordinary regression models.

Fit measure	Model		
	Fitted model[1]	Saturated model[2]	Ordinary regression[3]
Chi square	0.02		1287.06
Chi square p-value	0.89		0
Normed fit index (NFI)	1	1	0
Root mean square error of approximation (RMSEA)	0		0.386
Expected cross-validation index (ECVI)	0.006	0.006	3.13
ECVI lower bound	0.006	0.006	3.068
ECVI upper bound	0.007	0.006	3.193
Modified expected cross validation index (MECVI)	0.006	0.006	3.131

[1]The model presented in Figure 1. [2]Model that includes all possible paths. [3]The independent model that assumes no correlation between the independent variables.

Table 2. Regression weights indicating the relationship between radial growth and each independent variable for the combined data set (Maximum Likelihood Estimates).

Relationship	Maximumlikelihood estimates	Standard error	Critical ratio	P-value
Radius<---time	313.51	2.18	143.91	***
Radius<---temperature	23.74	12.64	1.88	0.06
Radius<---solar radiation	2817.03	220.03	12.80	***
Radius<--- relative humidity	63.76	5.75	11.09	***
Radius<---wind speed	1447.03	73.63	19.65	***

*** the p-value is less than 0.001.

positive indicating the existence of a positive relationship between radial growth and the climatic variables. The standardized regression coefficients are 0.832 (age of a tree), 0.012 (temperature), 0.092 (solar radiation), 0.076 (relative humidity) and 0.113 (wind speed). This suggests that the most important variable to explain radial growth is age of the tree. It is also estimated that the predictors of radius explain 79% of its variance. In other words, the error variance of radius is approximately 20.9% of the variance of radius itself.

Although the goodness of fit measures indicate that the fitted model (Figure 1) is a good fit (Table 1), the parameter estimates show that rainfall has no direct influence on the radial growth. An attempt was made to modify the fitted model (Figure 1) by making rainfall a required variable in the model. Such a modification procedure is called specification search (Leamer, 1978). The objective of specification search is to alter the original model in search of a model that is better fitting in some sense, and yields parameters having practical, and in this case biological significance, and substantive meaning. The path diagram for the first attempt at modification is presented in Figure 2. For this path analysis model, a good ‘goodness of fit’ was obtained. The calculated value of the chi-square statistics was 3.194 with one degree of freedom and a p-value of 0.074. However, the goodness of fit for the second fitted model (Figure 2) was not as good as the model fit shown in Figure 1. The parameter estimates for the second fitted model (Figure 2) suggest that rainfall had no direct significant effect. Therefore, no additional information was gained by modifying the path diagrams from that of Figure 1 to that of Figure 2.

The third attempt at specification search was to consider a model fit for the second fitted model (Figure 2) that excluded wind speed as an explanatory variable (Figure 3). The model fit was good and parameter estimates were significant. The regression weight for rainfall in the prediction of radial growth was significantly different from zero at the 0.001 level (two-tailed, Figure 3). This indicates that rainfall has a significant effect on the radial growth of trees in the absence of wind speed. For this model, it is estimated that the predictors of radial growth explain 78.2% of its variance. This is very close to the value obtained for the first model (Figure 1), which includes all the predictors in the model. The standardized regression coefficients were 0.859 (age of a tree), 0.042 (temperature), 0.096 (solar radiation), 0.026 (relative humidity) and 0.03 (rainfall). These standard regression coefficients indicate that age of the tree is the most important variable in determining the stem radial growth. Models fitted without temperature or tree age as

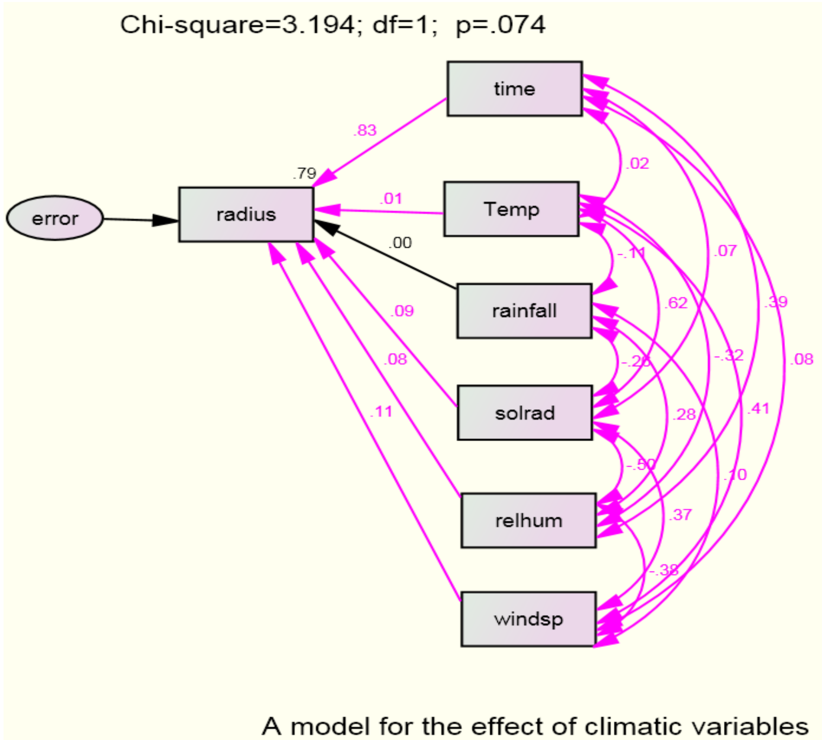

Figure 2. Path diagram showing the effect of age and climatic variables on radius of *Eucalyptus* clones when rainfall is considered a required variable. Time = age; solrad = solar radiation; relhum = relative humidity; windsp = wind speed.

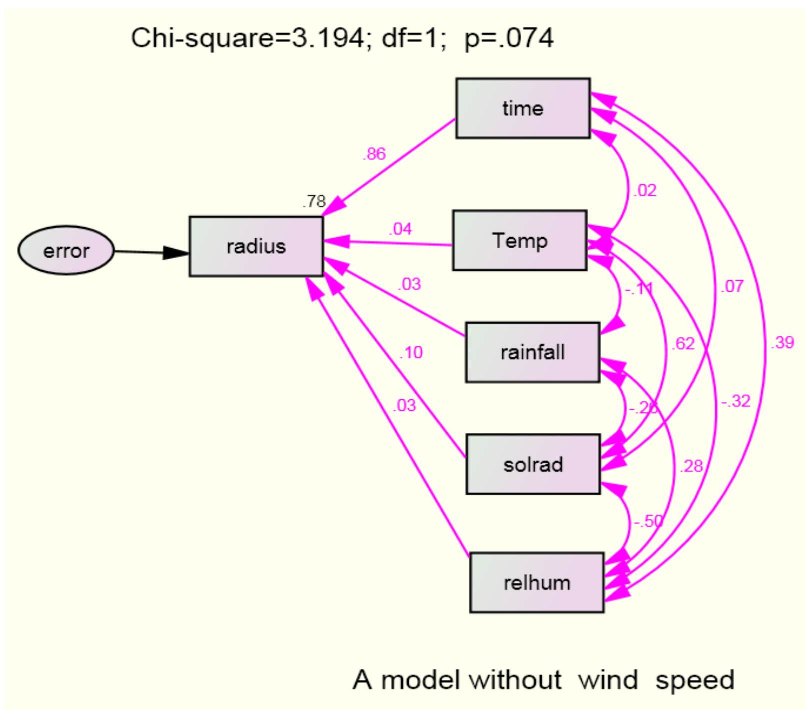

Figure 3. Path diagram showing the effect of age and climatic variables on radius of *Eucalyptus* clones when wind speed is omitted as an explanatory variable. Time = age; solrad = solar radiation; relhum = relative humidity.

explanatory variables did not fit well. A model that excluded relative humidity fitted well and resulted in rainfall having a significant effect on radial growth. The significance of rainfall in the absence of relative humidity and solar radiation was possibly caused by multicollinearity (where two or more predictor variables in a multiple regression model are highly correlated). The correlation among the climatic variables themselves is also significant. When only rainfall and wind speed were considered independent variables, the regression weight for rainfall became negative. The same occurred when only rainfall and relative humidity were treated as independent variables. This wrong sign of coefficients is an indication of possible multicollinearity. As a result, the effect of rainfall on radial growth cannot be completely ruled out, as its non-significance is possibly caused by multicollinearity. Some researchers noted that structural equation models are robust against multicollinearity (Malhotra et al., 1999), with some going as far as to explicitly state that Structural Equation Models (SEM) can remedy multicollinearity problems. For example, Maruyama (1998) argues that "structural equation approaches can help deal with some cases where the correlations among the predictors are large". On the other hand, some researchers have warned that multicollinearity can lead to SEM estimates being far from the true parameters, as well as the occurrence of large standard errors of the estimates (Jagpal, 1982; Grapentine, 2000). A simulation study by Grewal et al. (2004) showed some conditions under which multicollinearity caused problems. The study showed that when multicollinerity is extreme, type II error rate (accepting the null hypothesis when it is false) is generally, unacceptably high. They also indicated that for multicollinearity levels of between 0.6 and 0.8, type II error rates can be substantial (greater than 50% and frequently above 80%), if composite reliability is weak, explained variance (R^2) is low and sample size is relatively small. When multicollinearity levels are between 0.4 and 0.5, type II error rates tend to be quite small except when reliability is weak, R^2 is low and the sample size is small. In the present study R^2 values were large and the multicollinearity level was not high.

Estimates of regression weights for rainfall, which is important for growth, were inconsistent. Consideration of more complex models may improve results. In the path diagrams considered thus far only one dependent variable (radial growth) was used. Path analysis allows the simultaneous modeling of several related regression relationships. This means that path analysis can handle more than one independent variable in the model. Moreover, a variable can be a dependent variable in one relationship and an independent variable in another relationship of the path model. An attempt was made to fit a model where two dependent variables, namely rainfall and temperature, mediated the effects of relative humidity, solar radiation and wind speed. In this model, it was hypothesized that the age of a tree had a direct effect on radial growth. Solar radiation, relative humidity and wind speed were assumed to have an indirect effect. The fitted model is presented in Figure 4.

The value of the chi-square statistic is 862.7 with a p-value of zero. This indicates that the model does not fit the data well. However, the parameter estimates of the regression weights are all significant (Table 5). The magnitude of each effect is quantified by standardized regression coefficients. The standardized regression coefficients are 0.87 (age of the tree), 0.091 (temperature), and 0.018 (rainfall). From this it can be seen that the most important variable to explain radial growth is tree age. For the model in Figure 4 there are three structural equations, one for each of the three dependent variables: rainfall; temperature and radius. In terms of variable names, the structural equations are:

$$rainfall = relative\ humudity + solar\ radiation + wind\ speed + error\ 1$$
$$temperature = relative\ humudity + solar\ radiation + wind\ speed + error\ 2$$
$$radius = rainfall + temperature + time + error\ 3$$

This model includes direct effects (e.g. age of the tree on radial growth), indirect effects (e.g. effect of relative humidity through rainfall) and correlated independent variables (e.g. relative humidity, solar radiation and wind speed). The estimated model using AMOS statistical software is given by:

$$rainfall = 0.196\ relative\ humudity - 6.27\ solar\ radiation + 3.22\ wind\ speed$$
$$temperature = 0.017\ relative\ humudity + 8.77\ solar\ radiation + 1.39\ wind\ speed$$
$$radius = 20.73\ rainfall + 178.37\ temperature + 329.67\ time$$

From the fitted model (Figure 4) the positive effect of the predictors, rainfall, temperature and tree age can be seen. The standardized regression weights for this model indicate that tree age, temperature and rainfall are respectively important determinants of radial growth.

The data set to which the above models were applied was a combined data set (for both *E. grandis* hybrid clones). In order to see if there was any difference between the two clones, a multiple group analysis was used. In this regard, the good fitting model produced in Figure 1 and the model with multiple dependent variables (Figure 4) was considered. The good fitting model of Figure 1 was fitted to the data set for GU clone, alone. The model fitted the data very well. The value of the chi-square statistics was 0.06 with one degree of freedom and the corresponding p-value was 0.804. The next question to address was whether the same model fitted the data for the GC clone. Furthermore, the equality of the parameters needed to be tested. Instead of a separate group analysis, a single analysis that simultaneously estimated parameters and tested hypotheses about both groups was considered. This method provided a test for the significance of any differences found between the GU and GC clones. In addition, if there were no differences between the two

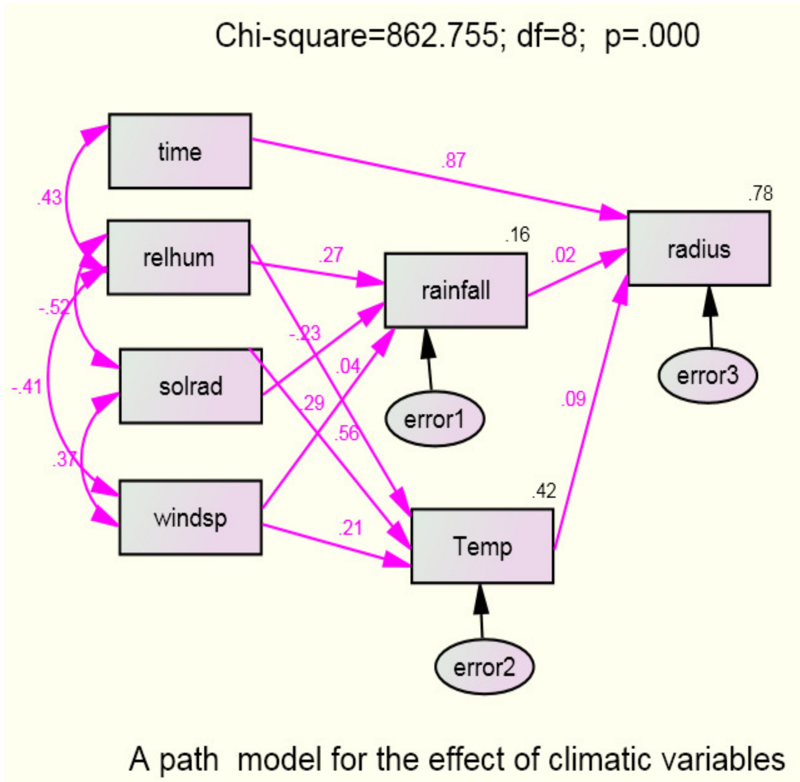

Figure 4. Path diagram showing the effect of multiple dependent variables (rainfall and temperature) on radial growth of *Eucalyptus* clones. Time = age; solrad = solar radiation; relhum = relative humidity.

clones, or if group differences concerned only a few model parameters, the simultaneous analysis of both groups would have provided more accurate parameter estimates than would have been obtained from separate single-group analyses. A test for pair wise path coefficient differences for the two clones was conducted. Some fit measures for various models were generated, together with fit measures for saturated and independence models are shown in Table 3.

The structural weight model specifies that the regression weights for predicting radial growth from the measured climatic variables and the age of tree were the same for the GU and GC clones. The unconstrained model is the model that assumes that all the parameters for the two groups are different. For the unconstrained model, the value of chi-square was 0.08 with the corresponding p-value equal to 0.96. This indicated that the unconstrained model fitted the data very well. The structural weight model with a chi-square value of 364.59 and with seven degrees of freedom was rejected at any conventional significance level, suggesting that the regression weights of the two clones were significantly different. The assumption that the regression weights for the exogenous variables were the same for both clones was not supported. The estimated regression weights for the unconstrained model are summarized in Table 4 and Table 5. When comparing the regression weights for the two clones, these were all positive, indicating a positive effect of the climatic variables as well as tree age on radial growth. In addition, regression weights obtained for the GU clone were larger than those obtained for the GC clone, indicating that the GU clone grows faster than the GC clone. Regression weights of the GU and the GC clones, for the multiple dependent model in Figure 4, were also compared. The regression weights for the two clones were significantly different. The results of this model also show that the GU has faster growth than the GC clone.

The maximum likelihood estimates given in Tables 4 and 5 require the data to be of a continuous scale and have a multivariate normal distribution. The approximate standard errors used in the inference were therefore produced based on formulae that depend on normality assumptions. Non-normality can lead to spuriously low standard errors, with degrees of underestimation ranging from moderate to severe. The consequences are that, because the standard errors are underestimated, the regression paths and factors / error covariances will be statistically significant, although they may not be so in the population (Byrne, 2001).

It is known that many data do not qualify for multivariate normality and the current data is no

Table 3. Summary of fits for various models including the structural weight model.

Model	Number of parameters	Chi-square	df	P-value	Chi-square / df
Unconstrained	54	0.08	2	0.96	0.04
Structural weights	49	364.59	7	0.00	52.09
Structural covariance s	28	364.59	28	0.00	13.02
Structural residuals	27	1293.58	29	0.00	44.61
Saturated model	56	0.00	0		
Independent model	14	29255.12	42	0.00	696.55

df = Degrees of freedom.

Table 4. Regression weights for the GU clone when the path model in Figure 1 was fitted to compare the two clones (Unconstrained).

Relationship	Maximumlikelihood estimates	Standard error	Critical ratio	P-value	Label
Radius<---time	341.88	3.33	102.81	***	b1_1
Radius<---temperature	43.34	19.30	2.25	0.025	b2_1
Radius<---solar radiation	3253.04	335.85	9.69	***	b3_1
Radius<---relative humidity	75.14	8.77	8.57	***	b4_1
Radius<--- wind speed	1570.35	112.39	13.97	***	b5_1

***indicates the p-value is less than 0.001.

Table 5. Regression weights for the GC clone when the path model in Figure 1 was fitted to compare the two clones (Unconstrained).

Relationship	Maximumlikelihood estimates	Standard error	Critical ratio	P-value	Label
Radius<---time	285.14	2.075	137.436	***	b1_2
Radius<---temperature	4.13	12.040	.343	0.732	b2_2
Radius<---solar radiation	2381.02	209.543	11.363	***	b3_2
Radius<---relative humidity	52.39	5.472	9.575	***	b4_2
Radius <---wind speed	1323.72	70.119	18.878	***	b5_2

*** indicates the p-value is less than 0.001.

exception. Using AMOS statistical software the data was checked to see whether it had a multivariate normal distribution. The Mardia's (1970) coefficient of multivariate kurtosis was 57.31 with a critical ratio of 237.3, which highly favours multivariate non-normality of the data.

A possible approach to overcome the problem of the existence of multivariate non-normal data is to use a method known as "bootstrap" (West et al., 1995; Yung and Bentler, 1996). This technique enables us to create multiple subsamples from an original data base. The importance of drawing these multiple samples is that we can examine parameter distributions relative to each of these newly produced samples. These distributions serve as a bootstrap sampling distribution and technically operate in the same way as the sampling distribution generally associated with parametric inferential statistics. In contrast to traditional statistical methods, however, the bootstrap sampling distribution is concrete and allows for comparison of parametric values over repeated samples that have been drawn (with replacement) from the original sample. The bootstrap method is free from the distributional assumptions and can be used to generate an approximate standard error for many statistics without having to satisfy the assumption of multivariate normality. With this beneficial feature in mind, the bootstrap method was applied to the good fitting model in Figure 1. In this process, 10,000 bootstrap samples were generated. The reported value of the chi-square was 0.018 with one degree of freedom. The bootstrap standard errors for regression weights are presented in Table 6. The table lists the bootstrap estimate of the standard error for each independent variable in the model. Each value represents the standard deviation of the parameter estimates computed across the 10,000 bootstrap samples. These values were compared with the values of the approximate maximum likelihood estimates presented in Table 2. Some discrepancies between the two sets of standard error estimates were observed. The third column of Table 6, labeled SE-SE provides the approximate standard

Table 6. Bootstrap standard errors for the path model in Figure 1.

Parameter (un-standardized)	SE	SE-SE	Mean	Bias	SE-Bias
Radius<---time	2.35	0.017	313.52	0.010	0.024
Radius<---temperature	12.55	0.089	23.85	0.11	0.125
Radius<---solar radiation	220.36	1.56	2816.58	-0.451	2.204
Radius<---relative humidity	5.89	0.042	63.75	-0.018	0.059
Radius<---wind speed	69.65	0.493	1446.07	-0.967	0.697
Standardized parameter					
Radius<---time	0.004	0.000	0.832	0.000	0.000
Radius<---temperature	0.006	0.000	0.012	0.000	0.000
Radius<---solar radiation	0.007	0.000	0.092	0.000	0.000
Radius<---relative humidity	0.007	0.000	0.076	0.000	0.000
Radius<---wind speed	0.006	0.000	0.113	0.000	0.000

Table 7. Ninety-five percent bootstrapped confidence intervals (bias-corrected percentile method).

Regression weights	Estimate	Lower	Upper	P
Radius<---time	313.51	308.86	318.03	0.000
Radius<---temperature	23.74	-1.21	48.76	0.060
Radius<---solar radiation	2817.03	2392.34	3252.47	0.000
Radius<---relative humidity	63.76	52.27	75.19	0.000
Radius<---wind speed	1447.03	1314.33	1588.51	0.000
Standardized regression weights				
Radius<---time	0.832	0.824	0.841	0.000
Radius<---temperature	0.012	-0.001	0.025	0.059
Radius<---solar radiation	0.092	0.078	0.106	0.000
Radius<---relative humidity	0.076	0.063	0.090	0.000
Radius<---wind speed	0.113	0.103	0.124	0.000

error of the bootstrap standard error itself. These values were very small indicating that the standard errors were estimated with a reasonable level of accuracy.

Column four, labeled mean, lists the mean parameter estimates computed across the 10,000 bootstrap samples. Arbuckle (2006) on page 301 emphasized that this bootstrap mean is not necessarily identical to the original estimate. Column five (Bias) represents the differences between the bootstrap mean estimates and the original estimates. These values are very small for most of the cases and positive values indicate that the estimates of the bootstrap samples are higher than the original maximum likelihood estimates. The low bias indicates that the maximum likelihood estimates and the bootstrap estimates are very close to each other. The last column, labeled SE-Bias, reports the approximate standard error of the bias estimate. For the majority of the cases the estimated bias is smaller in magnitude than its standard error. This indicates that there is little evidence that the regression weights are biased.

The bootstrap confidence intervals are presented in Table 7. The bias-corrected confidence intervals are used because these intervals are considered to yield more accurate values than percentile confidence intervals (Efron and Tibshirani, 1993). The confidence intervals for tree age, solar radiation, relative humidity and wind speed do not include zero. It can therefore be concluded that the regression weights of these dependent variables are significantly different from zero. The value of p in the 'p' column of Table 7 indicates that a 100(1-p)% confidence interval would have one of its end points at zero. In this sense, the p-value can be used to test the hypothesis that an estimate has a population value of zero. In this case the relationship between radius and temperature has a p-value 0.06, which means that a 94% confidence interval would have a lower boundary at zero. In other words, a confidence interval at any level less than 94% such as 90% or 92% would not include zero, and therefore reject the hypothesis that the regression weight is zero for a 90% confidence interval. For the relationship of radius with other independent variables the hypothesis at any conventional significance level such as 95 or 99% is rejected. Therefore, by applying the bootstrap method, it can be seen that the dependent variables had a significant effect on the radial growth of *Eucalyptus* trees. This result also agreed with the result obtained using the maximum likelihood method. It is also of interest to evaluate the appropriateness of the hypothesized model itself. Bollen and Stine (1993) provided a means of testing the null hypothesis that the specified model was correct. The Bollen-Stine bootstrap corrected p-value was 0.878. This corrected p-value indicates that the hypothesized model should not be rejected. This result is also in agreement with the maximum likelihood results. The other issue with the specified model was cross validation. To assess the validity of the model in Figure 1, expected cross validation index (ECVI) was applied. ECVI is proposed as a means to assess, in a single sample, the likelihood that the model cross-validates across similar size samples from the same population (Browne and Cudeck, 1989). It measures the discrepancy between the fitted covariance matrix in the analyzed sample, and the expected covariance matrix that would be obtained in another sample of equivalent size. Application of ECVI assumes a comparison of models, whereby ECVI index is computed for each model and then all ECVI values are placed in rank order. The model having the smallest ECVI value exhibits the greatest potential for replication. There is no determined appropriate range of values for ECVI as it can assume any value (Byrne, 2001). In the present case the values of ECVI are presented in Table 1. In assessing the hypothesized model, its ECVI value of 0.006 was compared with that of the independence model (ECVI=3.13). The ECVI for the saturated model was also 0.006. The ECVI for the hypothesized model was less than that of the independence model. It can therefore be concluded that the hypothesized model represents the best fit to the data. Furthermore, a 95% confidence interval for ECVI is given by [0.006, 0.007]. This indicates that of the overall possible randomly sampled ECVI values, 95% of them will fall [0.006, 0.007], suggesting that the model cross validates over the independent model.

Conclusions

Classical methods, like ordinary regression models once the regression model is specified, do not permit any other relationships among the independent variables to be specified. This limits the potential of the variables to have direct, indirect and total effects on each other. In path analysis one can see the direct effect, indirect effect and total effects of variables. In path analysis a unique additional contribution of each variable can be studied using the standardized regression weights. Even though we can study the additional contribution of each variable in multiple regressions, this can work ideally only if all independent variables are highly correlated with the dependent variable and uncorrelated among themselves. In contrast, path models provide theoretically meaningful relationships in a manner not restricted to a multiple regression model (Schumacker, 1991). In path analysis, we can estimate parameters for more than one regression equation because this analysis can be considered as a series of regressions applied sequentially to the data. Structural Equation Models (SEM) are considered as path analysis involving latent variables. In the present case, latent variables were not included and hence path models were generated. Path analysis was employed mainly because the climatic variables were correlated and the unique, additional contribution of each climatic variable on radial growth of eucalypts was of interest.

The best fitting path model generated in this study showed that all climatic variables and age of the tree had a positive effect on stem radial growth for the pooled data of both clones. Furthermore, all except one variable (rainfall) had a significant, direct effect on radial growth. It was also observed that the age of the tree was the most important variable explaining stem radial growth. Although rainfall was not significant in the best fitting model, it was found to be significant for the model that excluded wind speed and for the model that omitted solar radiation. This revealed that the effect of rainfall on radial growth cannot be ruled out. To compare the effect of the explanatory variables on the radial growth of the GU and GC clones, a single analysis that estimated parameters and tested hypotheses about both groups simultaneously was considered. The regression weights for the two clones were significantly different. The regression weights were all positive indicating the positive effect of the climatic variables as well tree age. In addition, the regression weights obtained for the GU clone were larger than the regression weights for the GC clone. This shows that the GU clone was growing faster than the GC clone which can easily be confirmed by looking at the growth of the two clones.

The main estimation method for path models, or any structural equation model (SEM) is maximum likelihood estimation. This method requires a distributional assumption, which the present data failed to satisfy. The bootstrap method was then applied to overcome the methodological failure due to non-normality. The estimated bias using the bootstrap method was very small showing that there was little evidence of bias in the estimates. The conclusion reached using the maximum likelihood method agreed with that of the bootstrap method. The expected cross-validation index obtained for the hypothesized model also showed that this model cross-validated over the independent model.

To sum up, the climatic variables measured in this study, together with tree age, had a positive effect on stem radial growth during the juvenile stage of development. Age of the tree was the most important variable in explaining stem radial growth. The growth of the GU clone was faster than the growth of the GC clone, possibly indicating that this clone has better genetic potential. However, this could also indicate that, compared to the GC clone, the GU clone is better adapted to the environmental conditions, or it is able to use the available resources more effectively.

ACKNOWLEDGMENTS

The authors are grateful to Dr Valerie Grzekowiak and Dr Nicky Jones for their valuable comments and suggestions.

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