Bulletin of the *Transilvania* University of Braşov
Series II: Forestry • Wood Industry • Agricultural Food Engineering • Vol. 10 (59) No.1 - 2017

MODELLING THE EFFECT OF TREE AGE AND CLIMATIC FACTORS ON THE STEM RADIAL GROWTH OF JUVENILE EUCALYPT CLONES

Sileshi F. MELESSE[1] Temesgen ZEWOTIR[1]

Abstract: *Tree growth is influenced by environmental and genetic factors. Trees with different genetic material growing under the same environmental conditions have different growth pattern. Adequate management requires good understanding of factors affecting tree growth. The aim of this study is to determine the factors that influences stem radial growth of juvenile Eucalyptus hybrids clones. The longitudinal data used in this study is obtained from Sappi land holdings in coastal Zululand of eastern South Africa. For the first two years of growth, measurements of stem radius were repeatedly obtained using dendrometer attached to 18 trees. Weekly measures of climatic data (temperature, solar radiation, relative humidity and wind speed) were simultaneously recorded with total rainfall from the site. A fractional polynomial model under linear mixed modelling framework, that incorporates the covariance structure into statistical model, was used. The results of the analysis indicate that the relationship between tree age and stem radius can be explained by a second degree fractional polynomial model. Subsequently, the model was extended to account for the effect of climatic variables. A significant difference was observed between the growths of the two clones. The results indicate that the effect of weather variables on stem radial growth depends on season. It is found that some weather variables (like temperature and solar radiation) that have positive effect in one season might have negative effect in another season. In conclusion, although tree age is the primary determinant of stem radial growth, weather variables are also found to have significant effect.*

Key words: *Dendrometer trial, Loess, longitudinal study, random slope.*

1. Introduction

Eucalyptus trees are woody plants that are essential and beneficial to humans. They are major sources of forest products and include commercially main woody plants for important oil production and the paper and pulp industry [22]. At the end of the twenty century, eucalyptus had become the most widely planted hardwood species in the world [33]. Most plantation trees are established and administered for profit; therefore, growth is an essential economic factor. Due to increasing wood consumption

1 School of Mathematics, Statistics and Computer Science, University of KwaZulu-Natal, South Africa.
Corresponding author: Sileshi F. Melesse; e-mail: Melesse@ukzn.ac.za.

and the development of pulp and paper production, plantations of fast growing tree species, managed with short rotations, have a growing importance for the sustainability of industrial wood raw material [22]. Eucalyptus trees are fast growing and can regrow from stumps after harvesting which makes multiple productions possible. Climatic factors such as temperature [9] sunlight, rainfall [9], [25], humidity [9] and wind speed [36] contribute to the growth of plants. Understanding the relationships between climatic variables and the pattern of stem growth would be helpful to know the suitable climatic conditions for tree growth.

Eucalyptus trees are among the most widely cultivated forest trees in the world [28]. Eucalyptus, together with species of *Pinus* and *Acacia*, species of *Eucalyptus* and *Corymbia* are among the trees most widely utilized to establish intensively managed plantations, particularly in the tropics and Southern Hemisphere [38]. Among countries of the world, Brazil has the highest Eucalyptus plantation cover (about 3 million hectare (ha)), followed by India and China who have Eucalyptus plantation cover of 1 million and six hundred thousand hectare respectively. South Africa has the largest area of Eucalyptus plantation in Africa. About half a million hectare (ha) is covered with Eucalyptus plantation [39]. The country is also known for its commercial Eucalyptus plantation. The majority of Eucalyptus plantations in South Africa (about 72%) are owned by companies and small growers [3]. Commercial planting of Eucalyptus has been operational for more than a century [38]. Therefore, in South Africa, Eucalyptus plantation has long been recognized as an important source of revenue.

E. gradis species is the most widely commercially grown species in South Africa. According to [27], about 73.8% percent of the total commercial forestry is covered by this species. *E. grandis* is traditionally an indispensable pulpwood species due to its fast growth and well – studied wood properties [32]. However, it is less resistance to drought and cold.

On the other hand, slow growing species, *Eucalyptus camaldulensis*, can be adaptable in drought and cold conditions. The rapid demand for hardwood for forest industry, has necessitated South Africa to embark on expansion of hardwoods into colder sites where *E. grandis* might not survive. Using crosses of *E. gradis* with *Eucalyptus camaldulensis* and *Eucalyptus urophylla was* considered as one of the solutions to meet the need for commercial forestry sector. These hybrids are also found to be adaptable and perform better than *E. gradis* to poor sites [16], [22], [34].

Modelling juvenile tree growth is important in forest management to determine timber yield and long-term response of forest structure and dynamics to selective logging [2], [10], [13]. The greatest potential for improving growth rates is during juvenile development [37]. Appropriate juvenile development modelling is crucial for simulation models [12]. For a given species the average juvenile tree growth is usually expressed as a function of age. However, such average growth models assume a constant and negligible variability of the given species trees. The juvenile growth data have shown a high variability growth even with the same hybrid clone of trees. Understanding the relationship between weather variables and the stem radial growth would facilitate the prediction of wood properties for a given cite [19]. Studies that are available so far focus on growth rate and pattern of growth as a function of age [5], [17], [20], [24]. The study [19] consider daily measurements of stem radius and the longitudinal aspect of the data was not taken into account. The current study attempts to take into account the longitudinal nature of the data and study the relationship between stem radius and weather variables.

Therefore, the main objective of this paper is to study the effect of climatic factors on the radial measure using a longitudinal data modelling approach.

2. Materials and Methods

2.1. Data

A dendrometer trial, which focused on the growth of a *Eucalyptus grandis* × *E. urophylla (GU*) and an *E. gradis* × *E. camaldulensis (GC)* hybrid clone, was established on Sappi landholdings at KwaMbonambi in the coastal Zululand area in the eastern part of South Africa. Sappi South Africa is a forest product company operating in the country including the province of Kwazulu Natal. The research site is located near the town of KwaMbonambi (28.53º S, 32.14º E, 55 m AMSL) approximately, 200 km north-east of the city of Durban. On average, the site receives 1,000 mm of rainfall per year, and has a mean annual temperature of 21°C. Most annual rainfall is usually received in spring and summer, with dry winters [8], [19].

The trial was designed to run over separate growth monitoring phases. Each phase ended with the destructive sampling of study trees in order to measure several wood characteristics. The results presented in this study are based on the data collected only during the first of these phases of growth. The first phase ran from April 2002 when trees are 39 weeks–old until August 2003 when trees were 107 weeks old.

Using dendrometers repeated measurements of stem radius were obtained, during this time, for a sample of 18 trees, nine from each clone. A detailed soil survey of the site conducted in August 2001 showed that the site was very uniform, thus minimizing the potential manifestation of unexpected or anomalous growth characteristics. Planting began on 16 July 2001. The site preparation prior to planting, in April 2001, included the treatment of tree stumps from the previous rotation with herbicide (to prevent coppicing) and slash from the previous harvest was burned. Each rooted cutting was established in pre-prepared soil pits between existing stumps, together with approximately 2 liters of water. The two clones were planted in alternating columns of 7 × 24 trees at a 3 m × 2.5 m spacing. Within each column of trees for a particular clone, three plots of 12 trees (4×3), each with two surrounding tree rows were demarcated. The plots were established in pairs, so that in any phase of the research a GU and a GC plot could be measured simultaneously. Nine trees per plot were selected from each clone for intensive monitoring of radial growth [7], [8], [18], [19], [20]. From the 18 sampled trees (nine per clone), longitudinal data of 1242 weekly average radial measurements were obtained.

The response variable investigated in this study was the weekly stem radial growth, which is of interest because it can be used to understand the underlying processes of fibre development in fast-growing Eucalyptus plantations. 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 (ºC), relative humidity (%), solar radiation (mJ/hr,), rainfall (mm) and wind speed (m/s). The weekly total rainfall and the weekly average of other climatic variables were obtained from the hourly data by cumulating and averaging the hourly measurements.

2.2. Methods

Cross sectional study may allow comparison among subpopulations that happen to differ in age, but it does not provide any information about how individuals change over time. The assessment of within subject changes in response over time can only be achieved within a longitudinal study [20]. A distinctive feature of longitudinal data is that observations within the same individual are correlated. Failure to account for the effect of correlation can result in an erroneous estimation of the variability of parameter estimates and hence in misleading inference. This interdependence can be modeled using mixed models. The current data set consisted of repeated measurements of the same subjects over time, therefore, a mixed effects models approach was adopted [11], [23], [26], [35] in the analysis of the longitudinal data.

Models for the analysis of such data recognize the relationship between serial observations on the same unit. Since change in stem radial growth, which is a continuous response variable, is the main object of the study, it is of interest first to study the mean effect of time alone on the stem radial growth without correcting for climatic factors that can influence the pattern of response. We also adopted the fractional polynomial approach to the mixed model by using a polynomial regression model with parameters that are allowed to vary over individual trees, and which are therefore called random effects or tree-specific regression coefficients [14], [30]. Their mean then reflects the average evolution in the population of trees.

2.3. Selection of a Preliminary Mean Structure

The plot of an individual tree's stem radial growth and the Loess smoothed curve suggest that the relationship between the radial measure and tree age is curved (Figure 2). The presence of curvature can be handled by using conventional polynomials. In most applications the choice is made between linear and quadratic terms, with cubic or higher order polynomials being rarely used or useful. It has long been recognized that conventional polynomials (which offer only few curve shapes) do not fit the data well. High order polynomials (sometimes even cubic polynomials) follow the data more closely but often fit badly at the extremes of the observed range of the independent. The [30] approach was adopted. This is based on the fractional polynomials and a unified description and a degree of formalization. We considered a second degree fractional polynomial model of the form:

$$\alpha_o + \alpha_1 t^p + \alpha_2 t^q \quad for\ p \neq q$$

$$\alpha_o + \alpha_1 t^p + \alpha_2 t^p \ln(t) \quad for\ p = q$$

The parameter α_0 stands for the intercept while α_1 and α_2 are the slopes associated with power p and q respectively. The variable t stands for tree age. The powers p and q are chosen from among -2, -1,-0.5, 0, 0.5, 2 and 3. This set includes linear, reciprocal, square root, square and cubic transformations and their combinations. The best fit among the possible 36 combinations of such powers is defined as that which maximizes the likelihood function. Such second degree fractional polynomials offer considerably more flexibility and accommodate many functions with single turning points as well as j shaped relationships (see for example, [15], [31]. The best fitting fractional polynomial curve for the current data is found to be the curve with powers *p=1* and *q=0.5*. That is the linear term plus a square root of time. The preliminary graphical analyses also indicated that the intercept and growth patterns were different for different trees. Therefore, having a different slope for each tree, leads to subject- specific regression coefficients, which represent the random effect in the mixed model. The provisional model for stem radial growth as a function of time (tree age in weeks) is:

$$Y_{it'} = \beta_{0i} + \beta_{1i}\, t' + \beta_{2i}\, t'^{1/2} + \varepsilon_{it'} \qquad i = 1,2, \ldots 18 \tag{1}$$

The dendrometer measurements began when the tree was about 39 weeks of age. The actual age, t, of the tree differs from the dendrometer age, denoted by t', by 39 weeks. In other words, $t' = t - 39$, where: t' and t are the dendrometer and actual ages, respectively, of tree i. $Y_{it'}$ is the radial measure of the i^{th} tree at age t'_i, β_{1i} is the coefficient of time effect for the i^{th} tree, β_{2i} is the coefficient of the square root of time effect for the i^{th} tree, $\varepsilon_{it'}$ is the mean zero deviation which represents the within-tree variability, β_{0i} represents the mean radial size of tree i at the beginning of dendrometer measurements, that is when $t' = 0$. The values β_0, β_1 and β_2 and are the average intercept, coefficients of time and square root of time effects, respectively, of the population. After correcting for the effect of individual characteristics the individual coefficients can then be expressed as:

$$\beta_{0i} = \beta_0 + b_{0i}$$
$$\beta_{1i} = \beta_1 + b_{1i}$$
$$\beta_{2i} = \beta_2 + b_{2i}$$

For the i^{th} tree, the terms b_{0i}, b_{1i} and b_{2i} represent the random deviations of the intercept, coefficients of time and square root of time, respectively, from the corresponding population parameters β_0, β_1 and β_2. Therefore, model (1) can be rewritten as:

$$Y_{it'} = (\beta_0 + b_{0i}) + (\beta_1 + b_{1i}) \cdot t' + (\beta_2 + b_{2i}) \cdot t'^{1/2} + \varepsilon_{it'} \tag{2}$$

equivalently to:

$$Y_{it'} = \beta_0 + \beta_1 \cdot t' + \beta_2 \cdot t'^{1/2} + b_{0i} + b_{1i} \cdot t' + b_{2i} \cdot t'^{1/2} + \varepsilon_{it'}$$

The matrix form of model (2) is:

$$Y_i = Z_i \beta + Z_i b_i + \varepsilon$$

where:

$$\mathbf{Y}_i = \begin{bmatrix} Y_{i_1} \\ Y_{i_2} \\ \vdots \\ Y_{i_n} \end{bmatrix} \quad Z_i = \begin{bmatrix} 1 & \sqrt{t_{i_1}} & t_{i_1} \\ 1 & \sqrt{t_{i_2}} & t_{i2} \\ \vdots & \vdots & \vdots \\ 1 & \sqrt{t_{in_i}} & t_{in_i} \end{bmatrix} \quad \beta = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \end{bmatrix} \quad b_i = \begin{bmatrix} b_{0i} \\ b_{1i} \\ b_{2i} \end{bmatrix} \quad \varepsilon_i = \begin{bmatrix} \varepsilon_{i_1} \\ \varepsilon_{i_2} \\ \vdots \\ \varepsilon_{in} \end{bmatrix}$$

Model is a mixed model with fixed effects β and random effect $\boldsymbol{b}_i$. The random effects $\boldsymbol{b}_i$ are assumed to be normally distributed with mean vector $\boldsymbol{0}$ and (3×3) covariance matrix $\boldsymbol{D}$ where:

$$\mathbf{D} = \begin{bmatrix} d_{11} & d_{12} & d_{13} \\ d_{21} & d_{22} & d_{23} \\ d_{31} & d_{32} & d_{33} \end{bmatrix}.$$

Likewise the vector of residuals ε_i is assumed to be normally distributed with mean vector $\boldsymbol{0}$ and (n × n) covariance matrix, $\boldsymbol{\Sigma}_i$. Assuming the random effects and error terms are independent, the marginal distribution for the vector of responses of the i^{th} tree, $\boldsymbol{Y_i}$ is normally distributed with mean vector $\boldsymbol{Z_i\beta}$ and variance covariance matrix given by:

$$V_i = Z_i D Z'_i + \sum\nolimits_i$$

3. Results and Discussions

3.1. Exploratory Data Analysis

Box plots of the stem radius with respect to each tree (the tree numbers are given during the experiment) are presented in Figure 1.

Some variability in mean stem radius for different trees evidently observed.

The between tree variability is clearly seen from this plot. Moreover, the within tree variability is not the same for all trees. The modelling process needs to take into account all of the information obtained during the visualization process.

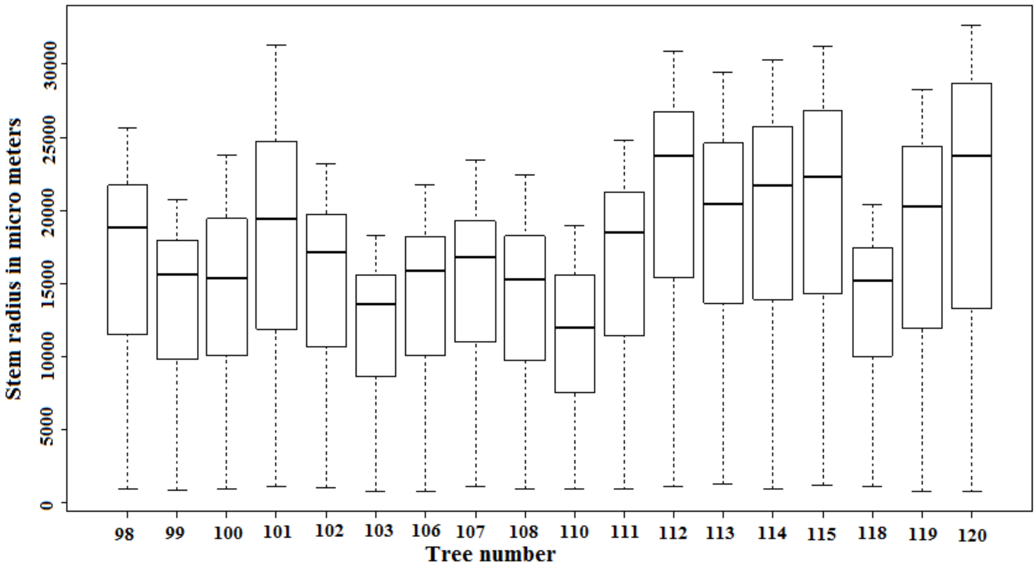

Fig.1. *Box plot of stem radius expressed in micro meters for 18 trees*

The loess smoothing technique by [4] is used to study the functional relationship between radial growth and tree age. Figure 2 [20] shows that radial measurements were initiated at about 40 weeks of age (when the dendrometers could be attached to the trees without causing damage). It shows a sharp increase in the estimated mean response profile of the stem radius from the beginning (39 weeks) up to the age of 70 weeks, and thereafter the rate of increase slows down for both clones.

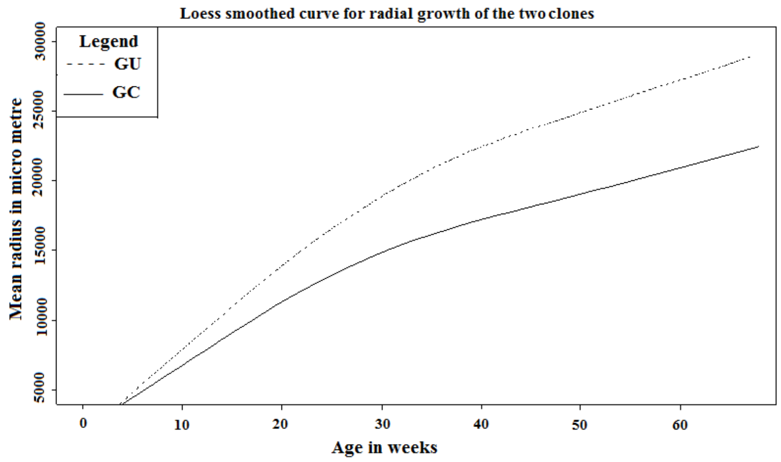

Fig. 2. *Loess smoothed curves of stem radial measure (in micro meters) against time for both clones*

3.2. Exploring the Covariance Structure

Random effects are effects that arise from the characteristics of individual trees. Therefore, these effects explain the stochastic variation between trees. On the other hand, measurements of stem radius, on successive occasions of the same tree, are most likely to be serially dependent. Hence, we cannot extract as much information from these dependent observations as we could from the same number of independent measurements. That is, serial correlations mask part of the within tree variation in the data. The possibility of measurement error cannot be ignored. That is, during data collection, measurement error is expected. Therefore, these three sources of variability were considered in further analysis.

The covariance structure models all variability in the data which cannot be explained by set of explanatory variables [35]. An attempt to obtain residuals after removing all systematic trends was made. The analysis of such residual suggested that the variance of the response variable is not constant.

For balanced longitudinal data, the correlation structure can be studied through the correlation matrix, or a scatter plot matrix. In our case, we considered the weekly radial measure for some weeks to see how the correlations among repeated measurements of the data behave. The stem radial measures for weeks 39, 40, 41, 60, 70, 100, 101 and 102 were considered. The estimated correlation matrix for these selected time points is presented as follows:

$$\begin{bmatrix} 1 & 0.90 & 0.83 & 0.33 & 0.24 & 031 & 0.31 & 0.30 \\ 0.90 & 1 & 0.97 & 0.54 & 0.45 & 0.50 & 0.50 & 0.49 \\ 0.83 & 0.97 & 1 & 0.61 & 0.50 & 0.54 & 0.54 & 0.54 \\ 0.33 & 0.54 & 0.61 & 1 & 0.98 & 0.91 & 0.91 & 0.92 \\ 0.24 & 0.45 & 0.50 & 0.98 & 1 & 0.93 & 0.93 & 0.93 \\ 0.31 & 0.50 & 0.54 & 0.91 & 0.93 & 1 & 0.99 & 0.99 \\ 0.31 & 0.50 & 0.54 & 0.91 & 0.93 & 0.99 & 1 & 0.99 \\ 0.31 & 0.49 & 0.54 & 0.92 & 0.93 & 0.99 & 0.99 & 1 \end{bmatrix}$$

The correlation between measurements at week 39 and week 40 is 0.9 indicating a strong relationship between the measurements of week 39 and week 40. On the other hand the correlation between the measurements of week 39 and week 102 is only 0.3. This shows that there is a strong correlation between measurements that are at closer time points to each other. The correlation is dying as the length of time between two measurements increases.

The exploratory analyses suggested that the stem radial growth is increasing over time. However, the rate at which it is increasing is different for the two clones. Moreover, the exploration of the covariance structure shows that there is a clear indication for the between tree and within tree variability. It was also established that the stem radius data is balanced and free from the problem of dropout. This paves the way for justifiability of likelihood based analysis. The above exploratory analysis suggested, the demand for a "tree effect" in the model, which is indeed the motivation for mixed effects models. The plot of an individual tree's stem radius (not shown here) and the Loess smoothed curve (Figure 2) suggest that the relationship between the radial measure and tree age is curved. The multivariable fractional polynomial (**mfp)** package in R statistical software [1] was used to select the mean structure of the model used in this study. The best fitting fractional polynomial curve for the current data is found to be the second order fractional polynomial with powers $m_1 = 0.5$ and $m_2 = 1$ [21], [30]. That is the linear term plus a square root of time.

3.3. Selection of Random Effects

The inferential focus of this study is on the mean response of the stem radial measure. In order to have a valid inference about the mean structure, the covariance structure must be incorporated into the statistical model. In this type of longitudinal data there are at least three possible components of variability: random effects, serial correlation and measurement error [6].

Following the selection of the mean structure, the selection of the random effects was performed. That is, the assessment as to which of the curve components (the intercept, time or square root of time), should have a random component was made. Initially, a linear mixed model was fitted, assuming the diagonal elements in Σ_i are all equal and the off-diagonal elements are zero. Therefore, the variance of the response vector Y_{it}' depends on time only through the component Z_iDZ_i'. A hierarchical test procedure was followed to see if any of the random effects could be removed from the model. Hence the test begins with the inquiry as to whether or not the square root of time effect differs between trees. The formulation of the test of hypothesis at a specified α-level of significance is:

H_o: $d_{13} = d_{23} = d_{33} = 0$ against the alternative:

H_a: at least one of the d_{i3} is different from 0, i = 1, 2, 3.

In the above d_{13}, d_{23} and d_{33} are the covariance of random intercept and square root of time random effect, the covariance of time coefficients and square root of time coefficients and the variance of square root of time random coefficients respectively. The classical likelihood based inference cannot be applied for testing the above null hypothesis since the null hypothesis ($d_{33} = 0$) is on the boundary of the parameter space. To avoid this boundary value problem the asymptotic mixture of chi-squared distributions for the likelihood ratio test statistics was applied. This statistic is the difference of minus twice the logarithm of the likelihoods under the null and the alternative hypothesis. A large value of this difference rejects the null hypothesis and favors the alternative hypothesis, that there is a significant improvement in the fit when the extra random effect parameters are included [21].

The following random effect models were considered for testing:

- Model 1: Intercept, time, square root of time;
- Model 2: Intercept, time;
- Model 3: Intercept, square root of time;
- Model 4: Time, square root of time;
- Model 5: Intercept only.

The test results (using the asymptotic mixture of chi-square distributions) yield p-values less than 0.0001. We conclude that model one (intercept, time and square root of time) is preferable model among models listed above. The estimated general positive definite covariance matrix for the selected model is:

$$\hat{D} = \begin{bmatrix} 1127600 & -889950 & 53266 \\ -889950 & 779260 & -48320 \\ 53266 & -48320 & 5754 \end{bmatrix}$$

Investigation of standardized residuals indicates that the residual variability for the GU clone is larger than for the GC clone. A heteroscedastic model that allows different variances by clone was applied. Several variance functions discussed by [29] were applied for the variance of the within- tree error. Among the variance functions considered, a variance which is an exponential function of time was found to be the best fit.

That means the two clones had different variances and their variance was a function of tree age. The estimated standard error for the GC clone is about 76% of that for the GU clone. The estimate for fixed effects is similar to the estimates of the homoscedastic model. The estimates of fixed effects are presented in Table 1.

As seen from Table 1, the interaction of time effect with clone GC was not significant and hence was removed from the model. The interaction between clone and the square root of time effect is significant. This indicates that the two clones have different coefficients for the square root of time. Therefore, the longitudinal growth of the GU clone is significantly higher than that of the GC clone.

Further examination of residuals shows that the standardized residuals are small; suggesting that the mixed effects model with heteroscedastic variance is successful in explaining the radial growth curves.

The homoscedastic model and the heteroscedastic model are also compared using a formal test. The results of the formal test confirm that the heteroscedastic model explains the data significantly better than the homoscedastic model. The maximum likelihood estimates for the fixed effects of the heteroscedastic model, after removing the interaction effect of clone and time, are presented in Table 2.

Fixed effect estimates for heteroscedastic model Table 1

Effect	Value	Standard error	t-value	P-value
Intercept	-5547.85	812.91	-6.82	0.001
Time	-137.39	38.62	-3.36	0.001
Clone (GC)	2738.96	1122.49	2.44	0.026
$\sqrt{time}$	5072.58	462.64	10.96	0.001
$\sqrt{time}$ × Clone (GC)	-1514.95	648.76	-2.33	0.019
Clone (GC) × time	84.26	54.17	1.56	0.12

Table 2

Maximum likelihood estimates for the parameters of the fitted model

Effect	Parameter	Estimated Value
intercept	β_0	**-4762.79**
Time	β_1	**-94.44**
$\sqrt{time}$	β_2	**4614.43**
clone (GC)	β_3	**1220.95**
$\times \text{clone}(\text{GC}) \times \sqrt{time}$	β_4	**-618.06**

Therefore the fitted marginal model, or the average profile of the radial measure at tree age of ‘*t*` for the two clones can be summarized as follows:

$$\hat{Y}_{t'} = -3541.84 - 94.44\ t' + 3996.37\sqrt{t'} \quad \text{for GC clone}$$
$$\hat{Y}_{t'} = -4762.79 - 94.44\ t' + 4614.43\sqrt{t'} \quad \text{for GU clone}$$

3.4. The effect of climatic variables

The above fitted fractional polynomial models are extended to include the effect climatic variables and their interaction with clone. The effect of each climatic variable together with the interaction between clone and each climatic variable is considered in the modelling process. The results of the fixed effect estimates are presented in Table 3.

Fixed effect estimates for the model that includes the effect of weather variables Table 3

Covariates	Value	Standard Error	t-value	p-value
Intercept	-5764.61	669.58	-8.6	0.0000
Time	45.45	24.26	1.87	0.0600
Clone (GC)	2085.67	538.27	3.87	0.0010
$\sqrt{time}$	3095.81	322.69	9.59	0.0000
Temperature	39.58	11.09	3.57	0.0004
Rainfall	3.72	0.96	3.86	0.0001
Relative humidity	15.40	4.98	3.09	0.0020
Solar radiation	2381.09	246.63	9.65	0.0000
Wind speed	818.52	67.27	12.17	0.0000
Clone $\times \sqrt{time}$	-612.89	281.70	-2.18	0.0298
Clone × Temperature	-48.91	14.18	-3.45	0.0006
Clone × Solar radiation	-669.98	302.85	-2.21	0.0271

The interaction effect of clone with each climatic variable is studied one by one.

The hierarchical procedure is used to test for additional parameter in the model. Clone is found to have significant interaction with temperature and solar radiation. The interaction of clone with other climatic variables is not significant. Temperature appears to have an opposite effect on the radial growth of the two clones. The rest of the weather variables appear to have positive effect on the stem radial growth. However, the above result is without considering the effect of season on the weather variables.

The effect of weather variables might depend on season. The effect of weather variables on stem radius is considered after including season as one of the factor that determine stem radial growth. The results of the model that include season are presented in Table 4.

Fixed effect estimates for the model that includes the effect of season Table 4

Covariates	Value	Standard Error	t- value	p-value
Intercept	2623.54	1576.26	1.66	0.0963
Time	59.22	27.31	2.17	0.0303
Clone (GC)	2177.79	578.60	3.76	0.0017
$\sqrt{time}$	3014.48	357.36	8.44	0.0000
Temperature	33.46	24.57	1.36	0.1735
Rainfall	22.95	2.83	8.12	0.0000
Relative humidity	-50.15	10.83	-4.63	0.0000
Solar radiation	1274.96	285.45	4.47	0.0000
Wind speed	-371.84	163.67	-2.27	0.0233
Clone $\times \sqrt{time}$	-612.31	285.85	-2.14	0.0324
Clone × Temperature	-54.63	9.06	-6.03	0.0000
Clone × Solar radiation	-609.67	195.40	-3.12	0.0019
Season (Autumn)	-6983.10	1553.89	-4.49	0.0000
Season (Winter)	-13145.67	1537.28	-8.55	0.0000
Season (Spring)	-2281.52	2044.41	-1.12	0.2647
Temperature × Season (Autumn)	87.22	26.06	3.35	0.0008
Temperature × Season (Winter)	58.71	26.56	2.21	0.0270
Temperature × Season (Spring)	-8.41	28.26	-0.29	0.7658
Rainfall × Season (Autumn)	-16.84	3.60	-4.68	0.0000
Rainfall × Season (Winter)	-24.63	2.91	-8.47	0.0000
Rainfall × Season (Spring)	-21.31	3.26	-6.54	0.0000
Wind speed Season (Autumn)	284.17	199.27	1.43	0.1541
Wind speed × Season (Winter)	730.49	180.05	4.06	0.0001
Wind speed × Season (Spring)	255.05	255.19	0.99	0.3178
Solar radiation × Season (Autumn)	-489.65	363.35	-1.35	0.1780
Solar radiation × Season (Winter)	6053.74	462.14	13.09	0.0000
Solar radiation × Season(Spring)	-459.05	386.76	-1.19	0.2355
Relative humidity × Season (Autumn)	50.57	12.33	4.10	0.0000
Relative humidity × Season (Winter)	92.67	11.79	7.85	0.0000
Relative humidity × Season (Spring)	36.24	18.23	1.99	0.0471

Rainfall and solar radiation have positive effect on stem radial growth during summer (Table 4). The effect on temperature is negative for GC clone while no significant effect of temperature is observed for GU clone in summer. Wind speed and relative humidity appears to have negative effect on the stem radial growth of both clones during summer.

In autumn, the effect of rainfall, temperature, relative humidity and solar radiation on stem radial growth appears positive for both clones. The effect of wind speed is negative on the stem radial growth for both clones in autumn. In winter, temperature, relative humidity, solar radiation and wind speed have positive effect on the stem radial growth of both clones. The effect of rainfall on stem radius appears negative for both clones during winter. In spring, rainfall and solar radiation have positive effect on the stem radial growth for both clones. Relative humidity and wind speed have negative effect on the stem radial growth for both clones in spring. The effect of temperature on stem radial growth is negative for GC clone while no significant effect was observed for GU clone in spring. According to our results some weather variables have negative effect in one season and have positive effect in another season. For instance, temperature has positive effect on stem radial growth of both clones in autumn and winter. On the other hand, negative effect of temperature is observed in summer and spring for GC clone while no significant effect is observed for GU clone.

3.5. Model Checks and Diagnosis

The plots of the standardized residuals versus fitted values, by clone, were re-examined to assess the adequacy of the heteroscedastic model (Figure 3). The difference in variability of the residuals for the two clones has improved (less variability is observed). A possible outlier is observed for tree numbers 120 and 112 which might need further attention. Overall the standardized residuals are small, suggesting that the mixed effects model with the effect of climatic covariates included is successful in explaining the radial growth curves.

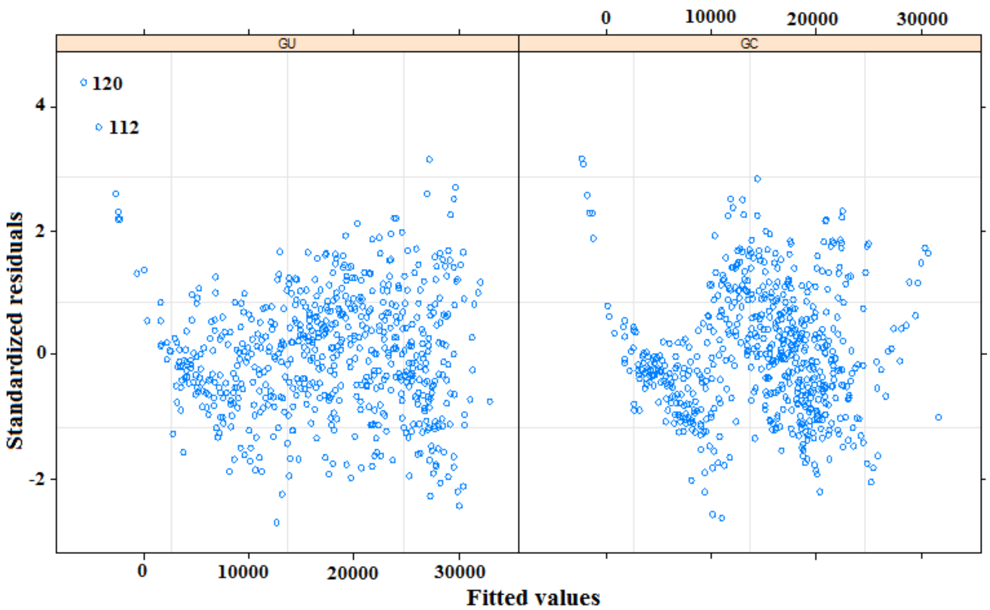

Fig. 3. *Plot of residuals versus fitted values by clone for the final model*

The assumption of normality for the within group errors was assessed using the normal probability plot of residuals. The normal probability plot of residuals is shown in Figure 4. Close examination of the behaviour of the two plots [40] shows that the normality assumption is plausible.

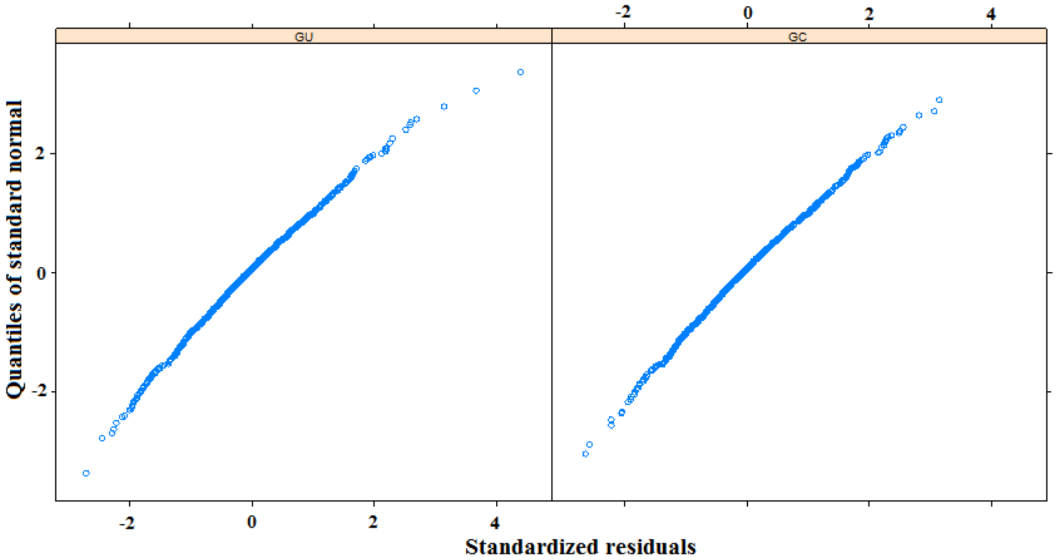

Fig. 4. *Normal probability plot of residuals by clone for the final model*

The investigation of the marginal normality of the corresponding random effects was also made. The assumption of normality seems reasonable for all three random effects.

The curves in Figure 2 suggest that the relationship between radial growth and age may be curvilinear (not linear). Based on descriptive and graphical exploratory analysis, an appropriate preliminary mean growth model is identified. The selected preliminary mean structure (the relationship between the mean and tree age) shows that radial measure is a function of linear time and the square root of time. Following the selection of mean structure, the selection of random effects resulted in the significance of all three random effects (namely, intercept, coefficients of time, and coefficients of square root of time). While selecting the unstructured covariance as covariance structure of random terms, a search for best structure for the covariance of the error component was made. The search resulted in the heterogeneous variance, which varies by clone and exponential function of square root of time, as the best fit. The growth pattern of the two hybrid clones is similar during the juvenile stage. The fractional polynomial models which were functions of tree age are extended to account for the effect of the climatic variables. Although tree age is the most important variable in determining the stem radial growth during the juvenile stage (up to two years), there is a significant effect of climatic variables on the stem radial change. Most of the climatic variables have positive effect on the stem radius during the juvenile stage of tree development. It was found that temperature has opposite effect on the radial growth of the two clones. The effect of temperature on the radial growth of GU clone is positive while it is negative for the GC clone. This could be primarily due to genetic variation between the two clones. Of course, this may entail further research in the area.

4. Conclusion

It appears that the average profile of the GU clone is higher than that of the GC clone with the difference becoming very apparent after the age of 50 weeks. Although only one clone from each hybrid cross was considered in this study, the faster growth characteristics of the GU clone indicates the improved genetics of this hybrid cross and its potential to better exploit available resources, making it more economically viable hybrid cross as reported elsewhere [20], [21], [22]. Tree age is the most important determinant of stem radial growth. Moreover, this study indicated that the effect of weather variable depends on season.

In winter, temperature, relative humidity, solar radiation and wind speed have positive effect on the stem radial growth. In autumn, rainfall, temperature, relative humidity and solar radiation have positive effect on the stem radial measure. This study is based on data collected at the juvenile stage of the *Eucalyptus* trees. The application of the same technique to adult trees and comparison of the results shall be the subject of future work.

Acknowledgements

The authors are grateful to Dr. Valerie Grzekowiak and Dr. Nicky Jones for several important comments and suggestions.

References

1. Benner A., 2015. Multivariable Fractional Polynomials (MFP). R package version 1.5.0.2014, 9 p.
2. Chazdon R.L., Finegan B., Capers R.S. et al., 2010. Composition and dynamics of functional groups of trees during tropical forest succession in northeastern Costa Rica. In: Biotropica, vol. 42(1), pp. 31-40.
3. CIFOR, 2000. Investing in the future: The private sector and sustainable forest management. A case study of progress towards sustainable forest management in the South African plantation forest industry. Center for International Forest Research, Bogor, Indonesia, 21 p.
4. Cleveland W.S., 1979. Robust locally weighted regression and smoothing scatterplots. In: Journal of the American Statistical Association, vol. 74(368), pp. 829-836.
5. Crecente-Campo F., Tomé M., Soares P. et al., 2010. A generalized nonlinear mixed-effects height–diameter model for *Eucalyptus globulus* L. in northwestern Spain. In: Forest Ecology and Management, vol. 259(5), pp. 943-952.
6. Diggle P.J., Liang K.Y., Zeger S.L., 1994. Longitudinal data analysis. New York: Oxford University Press, 5, 13.
7. Drew D.M., 2004. Dendrometer trial phase one technical report. Report No. EFR092T. Division of Water, Environment and Forestry Technology, CSIR, Pretoria, South Africa.
8. Drew D.M., Downes G.M., Grzeskowiak V. et al., 2009. Differences in daily stem size variation and growth in two hybrid eucalypt clones. In: Trees, vol. 23(3), pp. 585-595.
9. Eagleman J.R., 1985. Meteorology: The Atmosphere in Action. 2nd editon. Wadsworth Publishing Company, Belmont, California Co., pp. 17-284.
10. Finegan B., Camacho M., Zamora N., 1999. Diameter increment patterns among 106 tree species in a logged and silviculturally treated Costa Rican rain forest. In: Forest Ecology and Management, vol. 121(3), pp. 159-176.

11. Fitzmaurice G.M., Laird N.M., Ware J.H., 2004. Applied longitudinal analysis. John Wiley & Sons, New York, U.S.A., 740 p.
12. Gang Y., Weiqun C., Dongxiang L. et al. 2011. Growth and development simulation based on functional-structural model GreenLab for poplar (Salicaceae). In: African Journal of Agricultural Research, vol. 6(13), pp. 3071-3077.
13. Herault B., Ouallet J., Blanc L. et al., 2010. Growth responses of neotropical trees to logging gaps. In: Journal of Applied Ecology, vol. 47(4), pp. 821-831.
14. James G.M., Wang J., Zhu J., 2009. Functional linear regression that's interpretable. In: The Annals of Statistics, vol. 37(5A), pp. 2083-2108.
15. Long J., Ryoo J., 2010. Using fractional polynomials to model non-linear trends in longitudinal data. In: British Journal of Mathematical and Statistical Psychology, vol. 63(1), pp. 177-203.
16. Malan F.S., 1995. Eucalyptus improvement for lumber production. In: Anais do Seminario Internacional de Utilização da Madeira de Eucalipto para Serraria, São Paulo, Brazil, pp. 1-19.
17. Mateus A., Tomé M., 2011. Modelling the diameter distribution of eucalyptus plantations with Johnson's S B probability density function: parameters recovery from a compatible system of equations to predict stand variables. In: Annals of Forest Science, vol. 68(2), pp. 325-335.
18. Melesse S.F., Zewotir T., 2013a. The effect of correlated climatic factors on the radial growth of eucalypt trees grown in coastal Zululand of South Africa. In: African Journal of Agricultural, vol. 8(14), pp. 1233-1244.
19. Melesse S.F., Zewotir T., 2013b. Path models-approach to the study of the effect of climatic factors and tree age on radial growth of juvenile Eucalyptus hybrid clones. In: African Journal of Agricultural Research, vol. 8(22), pp. 2685-2695.
20. Melesse S.F., Zewotir T., 2015. Fitting three parameter growth curves using a nonlinear mixed effects modeling approach. In: South African Statistical Journal, vol. 49(2), pp. 223-240.
21. Melesse S.F., Zewotir T., 2017. Variation in growth potential between hybrid clones of Eucalyptus trees in eastern South Africa. In: Journal of Forestry Research. DOI 10.1007/s11676-017-0400-0.
22. Melesse S.F., Zewotir T., 2017. Comparison of two nonlinear curves to study the stem radial growth of eucalyptus tree. In: Baltic Forestry, vol. 23(2), pp. 438-448.
23. Meng S.X., Huang S., 2010. Incorporating correlated error structures into mixed forest growth models: prediction and inference implications. In: Canadian Journal of Forest Research, vol. 40(5), pp. 977-990.
24. Miehle P., Battaglia M., Sands P.J. et al., 2009. A comparison of four process-based models and a statistical regression model to predict growth of Eucalyptus globulus plantations. In: Ecological Modeling, vol. 220(5), pp. 734-746.
25. Miller G.T., 2001. Environmental Science: Working with the Earth, (Annotated Instructor's Version). Book/Cole Publishing House, Pacific Grove, C.A.
26. Molenberghs G., Verbeke G., 2000. Linear mixed models for longitudinal data. Springer-Verlag, New York.
27. Owen D.L., 2000. South African Forestry Handbook. 4th Edition. Volume 1. Southern African Institute of Forestry, Pretoria, South Africa, 416 p.

28. Pima N.E., Chamshama S.A.O., Iddi S. et al., 2016. Growth Performance of Eucalypt Clones in Tanzania. In: Environment and Ecology Research, vol. 4(3), pp. 146-154.
29. Pinheiro J.C., Bates D.M., 2000. Mixed-Effects Models in S and S-Plus. Springer-Verlag, New York, U.S.A., 537 p.
30. Royston P., Altman D.G., 1994. Regression using fractional polynomials of continuous covariates: parsimonious parametric modelling. In: Journal of the Royal Statistical Society. Series C (Applied Statistics), vol. 43(3), pp. 429-467.
31. Royston P., Ambler G., Sauerbrei W., 1999. The use of fractional polynomials to model continuous risk variables in epidemiology. In: International Journal of Epidemiology, vol. 28(5), pp. 964-974.
32. Stanger T.K., Galloway G.M., Retief E.C., 2011. Final results from a trial to test the effect of plot size on Eucalyptus hybrid clonal ranking in coastal Zululand, South Africa. In: Southern Forests: A Journal of Forest Science, vol. 73(3-4), pp. 131-135.
33. Turnbull J.W., 1999. Eucalypt plantations. In: New Forests, vol. 17(1), pp. 37-52.
34. Van Wyk G., Schonau A.P.G., Schon P.P., 1988. Growth potential and adaptability of young eucalypt hybrids in South Africa. In: Proceedings “Breeding Tropical Trees” IUFRO, Pataya, Thailand, pp. 348-358.
35. Verbeke G., Molenberghs G. (Eds.), 1997. Linear mixed models in practice: a SAS-oriented approach. Lecture notes in Statistics. Vol. 126. Springer-Verlag, New York, U.S.A.
36. Wadsworth R.M., 1959. An optimum wind speed for plant growth. In: Annals of Botany, vol. 23(1), pp. 195-199.
37. Watt M.S., Kimberley M.O., Richardson B. et al. 2004. Testing a juvenile tree growth model sensitive to competition from weeds, using *Pinus radiata* at two contrasting sites in New Zealand. In: Canadian Journal of Forest Research, vol. 34(10), pp. 1985-1992.
38. Wingfield M.J., Slippers B., Hurley B.P. et al., 2008. Eucalypt pests and diseases: growing threats to plantation productivity. In: Southern Forests: A Journal of Forest Science, vol. 70(2), pp. 139-144.
39. Zegeye H., 2010. Environmental and socio-economic implications of Eucalyptus in Ethiopia. In: Conference on Eucalyptus Species Management, History, Status and Trends in Ethiopia, at Addis Ababa, pp. 184-205.
40. Zewotir T., Galpin J.S., 2004. The behaviour of normal plots under non-normality for mixed models: theory and methods. In: South African Statistical Journal, vol. 38(2), pp. 115-138.