Research Article
doi: 10.1590/01047760202329013236
vol(29), 2023

CERNE

Parameter testing and application of the 3PG model for *Eucalyptus grandis* x *Urophylla* in subtropical conditions in South Africa

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FOREST MANAGEMENT

ABSTRACT

Background: The productivity of the coastal Zululand region, which was known as the South African breadbasket for fibre is declining. Climate-related changes are a significant factor contributing to this decline. The 3PG (Physiological Processes Predicting Growth) model was calibrated for *E. grandis x E. urophylla* hybrids planted in this region to quantify the effect of climate variation x site on their growth and survival. Monthly weather data for the ungauged plantations were estimated using the Random Forest (RF) supervised learning algorithm. A dataset consisting of 17 permanent sample plots (PSPs) and published parameter values for this hybrid in various regions of Brazil were utilized for parameter estimation. Using a parsimonious optimization approach, we developed a novel method called *extended Root Mean Square Error (eRMSE)* to select the optimal parameter set.

Result: The new parameter set yielded accurate predictions for three key variables; quadratic stem diameter (R^2 = 0.85, E = 0.73), mean height (R^2 = 0.84, E = 0.78), and basal area (R^2 = 0.87, E = 0.78). Model performance at 15 independent sites allowed the comparison with three other Brazilian parameter sets for stand volume prediction at a specific age. The optimized parameter set provided a satisfactory, albeit slightly overestimated stand volume (V (m^3ha^{-1}), R^2 = 0.65, E = -0.32) at the validation sites.

Conclusion: The 3PG model can be adapted with parameter set from another region to characterize the growth of E.grandis x E.urophylla stands in South Africa.

Keywords: Forest management, random forest, climate variation, process-based model.

HIGHLIGHTS

With local weather data, accurate estimates for ungauged plantations can be obtained.
The 3PG parameters can easily be calibrated from previously published parameter set.
Minimum ASW variable can be used to model growth on sites with groundwater access.
3PG model simulates tree growth dynamics in response to environmental changes.

GAKENOU, O. F.; MARTIN, K.C.; GERMISHUIZEN, I.; DREW, D. M. PARAMETER Testing and application of the 3pg model for *Eucalyptus grandis X urophylla* in subtropical conditions in South Africa. CERNE, V.29, e-103236, doi: 10.1590/01047760202329013236

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Received: March 1/2023 Accepted: June 23/2023

CERNE
ISSN 0104-7760
UNIVERSIDADE FEDERAL DE LAVRAS

INTRODUCTION

Global demand for wood continues to rise as the population grows (Brack, 2018). To ensure a continued, sustainable supply, afforestation using fast-growing species in areas of optimal growth may be the most viable alternative approach (Elias; Boucher, 2014). Clonal eucalypt forests have become important in this context due to their rapid growth rate, high wood quality, wide range of existing variability, and suitability to vegetative propagation (Rezende et al., 2014). The tropical *E.grandis* x *E.urophylla* hybrid has become an important plantation option and is widely planted in South Africa, as well as Australia, Brazil, China, India, Portugal, Spain, and Uruguay (Rezende et al., 2014).

In South Africa, this hybrid replaced *E. grandis* in the subtropical coastal Zululand region for commercial pulp production due to *E. grandis*' vulnerability to diseases and pests (Van Den Berg, 2017). The hybrid offers high productivity, short rotation, good survival rate, and suitability for pulp and paper production, making it valuable to pulp growers (Melesse; Zewotir, 2017). Furthermore, clonal forestry, including genetic and silvicultural improvements, was implemented in South Africa to increase the productivity of existing plantations and maintain low-cost wood production (Gardner, 2012).

Despite yield gains, the unpredictability of climate change and productivity shifts continue to pose limitations for commercial forest managers in their planning horizons (Drew, 2021). Climate, unlike genetics and management, is the only factor foresters cannot directly control, yet it plays a significant role in determining the increased productivity levels in *Eucalyptus* plantations (Binkley et al., 2017; Elli, 2020). South Africa is inherently prone to drought (Baudoin et al., 2017) and has a history of recurring dry periods (Xulu et al., 2018). The coastal Zululand region experienced a severe drought combined with an extreme El Niño event in 2014 – 2015 (Baudoin et al., 2017). Climate-related changes have been a particular issue in the coastal Zululand region, likely tied to the region's declining productivity. The commercial plantations in this region are intensively managed as short rotation forestry (8 – 12 years). Consequently, it becomes imperative to investigate the broad-scale impact of a rapidly changing environment on short rotation forestry.

The primary objective of statistical growth and yield models in forest management has been to develop prediction tools that assist in decision-making (Burkhart and Tomé, 2012). These model's relative simplicity and practicability have made them a default operational tool (Burkhart and Tomé, 2012). They have proven useful in providing quantitative insights for management and planning, predicting growth and yield, and providing product profile information (Landsberg; Sands, 2011). However, the mechanistic approach in forest modelling, which utilizes process-based models (PBMs) alongside weather/climate data, has gained significant attention from forest scientists (Elli, 2020). PBMs are structured to simulate stand growth based on the physiological processes driving growth and the impact of physical conditions on stands (Landsberg; Sands, 2011).

The 3PG (Physiological Processes Predicting Growth) model (Landsberg; Waring, 1997) is an interesting case, and perhaps one of the popular PBMs in forest science. It finds a niche in the continuum so that it is more considered a "hybrid model" (incorporating elements of both process-based and empirical models). This model has been calibrated and tested for various species in diverse forest types and geographic locations. Its application extends widely as both a research and operational tool (Gupta; Sharma, 2019). Specifically, the model has been calibrated and tested for *E.grandis* x *E.urophylla* hybrids in different regions in Brazil (Almeida et al., 2004; Stape et al., 2004; Borges et al., 2012), but not under South African conditions. Despite the potential of the 3PG model to serve as a decision support tool for accurate growth prediction and risk management in short rotation forestry, its operational use in the South African forestry industry remains limited (Dye et al., 2004; Esprey, 2006).

In regions like South Africa, where weather stations are scarce and sparsely distributed (Lynch, 2004), process-based growth modelling will always be constrained by the availability of reliable meteorological data. The coastal Zululand has a steep climatic gradient (Louw et al., 2011), and due to the inherent spatiotemporal variability of precipitation, high-resolution meteorological data is necessary to accurately capture environmental flunctuations. Unfortunately, no "off-the-shelf" products like the Australia's SILO resources (https://www.longpaddock.qld.gov.au/silo/) exist for South Africa. Moreover, the globally available gridded datasets are generated at a low spatial resolution, insufficient to capture the high level of spatiotemporal variability of rainfall on a local scale (Cáceres et al., 2018). Thus improved point estimates of weather data are critical for making informed and effective management decisions.

The study had the following objectives (1) address challenges in obtaining accurate weather data for ungauged plantations in South Africa, (2) Assess the need for a new parameter set for running the 3PG model with *E.grandis x E.urophylla* under South African conditions, and (3) test the 3PG model in a key commercial region in South Africa.

MATERIAL AND METHODS

General study area

Due to its commercial importance, the ready availability of site and management information, the existence of a strong precipitation gradient, and similar genetics planted across sites, the Zululand region of KwaZulu-Natal province was chosen for this study. The province is situated in the southeastern part of South Africa, encompassing 7.7% of the nation's total land area. The province exhibits a complex physiographic features resulting in a wide range of climatic conditions. The climate transitions from a subtropical climate near the coast to a temperate climate further inland. Notably, the Zululand region experiences an increase in precipitation from inland areas towards the coastal regions, as well as north to south

(Louw et al., 2011). The data were obtained from PSPs owned and managed by two forestry companies in South Africa: Mondi Forests (https://www.mondigroup.com) and Sappi (https://www.sappi.com) (Figure 1). Summary of the site and stand information is presented in Table 1. Also, 155 weather stations distributed across the KwaZulu-Natal province was used in the spatial interpolation of point estimate weather data for the unguaged plantations (Figure 2).

Description of the 3PG Model

The 3PG model is a simple, process-based, stand-level model that was originally developed for monospecific, even-aged, and evergreen forest (Landsberg; Waring, 1997), but has since further developed for deciduous, uneven-aged and mixed-species forests (Forrester; Tang, 2016). The model runs on a monthly time-step, and the data required to run the 3PG model can be divided into four classes; *weather data* (temperature, solar radiation, precipitation, atmospheric VPD, number of frost days in a month), *site information* (latitude, soil texture, atmospheric CO_2, and a simple fertility rating), *stand initialization data* (initial stocking, initial stem, root and foliage biomass, initial available soil water), and *species-specific parameters* (the main 3PG parameters consist of six major parameter classes which include biomass partitioning and turnover, Net Primary Productivity (NPP) & conductance modifiers, stem mortality, and stand characteristics). The output variables can be classified as follows: 1) State variables: biomass pools, stem number and plant-available soil water, 2) Stand-level outputs: stand basal area, stem volume, mean annual increment, and DBH, 3) Physiological and research-related variables: gross primary production, net primary production, stand evapotranspiration,and leaf area index, 4) Time-varying variables: growth modifiers, canopy quantum efficiency, light-use efficiency, etc.

Stand growth data

Tree-level diameter at breast height (DBH) and total height data for the study plots were obtained from two main sources. First from routine annual PSP re-measurements undertaken by the two forest companies involved in the study. Second, data for five plots were obtained from a set of band dendrometers installed in December 2013. In these five sites, DBH and stem number were measured every two weeks since the installation of the dendrometers, while total height measurements were taken annually. Height measurements were conducted on a subset of trees for each plot. The *forestmangr* package (Braga et al., 2021) was used to fit a Height-Diameter curve using the Weibull model (Equation 1) for estimating the height of non-measured trees. The data were grouped by site and age and the *nls_table* function was used to fit the H-D curve for all the sites at different age. In August 2018, a final set of measurements were taken at all sites. Where H is the height (m), D is the diameter at breast height, b_1, b_2, b_3 are the estimated model parameters.

$$H = 1.3 + b_1(1 - e^{(-b_2 D^{(b_3)})}) \quad (1)$$

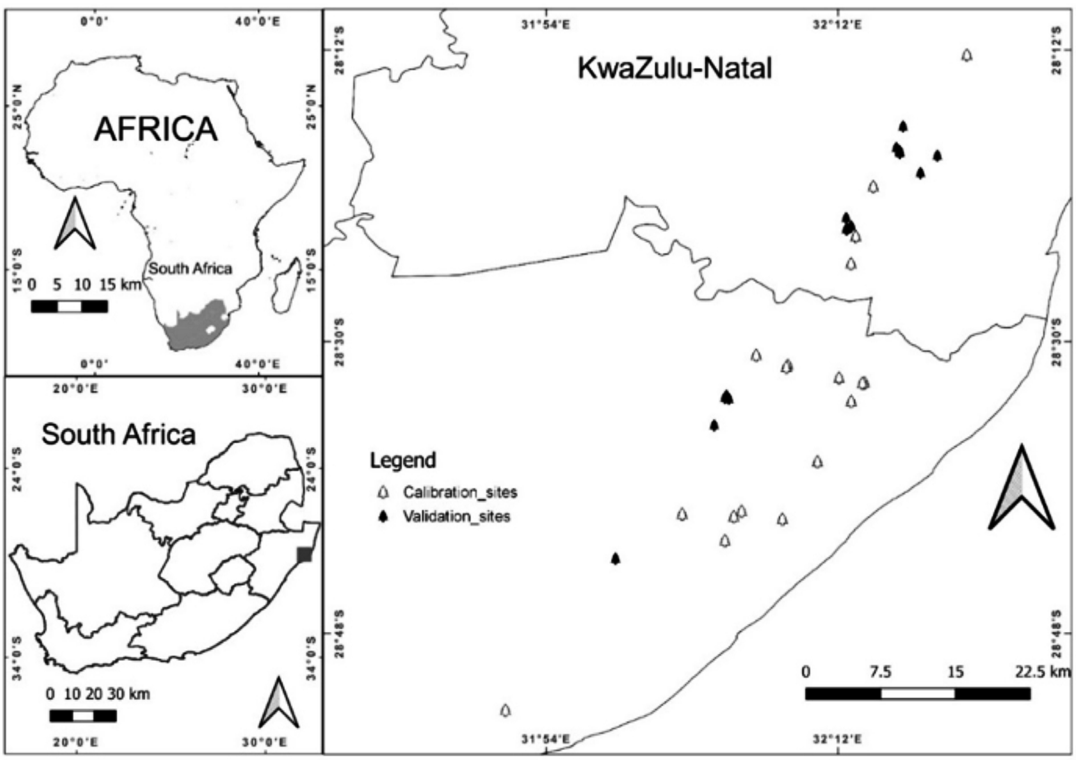

Figure 1: Map showing the extent of the permanent sample plots.

Table 1: Summary of site information used for model calibration and validation.

Company	Compartment name	Planted date	Measurement date	Age (Years)	Elevation (m)	Site index	Clone	Soil form	Type
Sappi	E6a	2010/08/15	2018/08/22	8.02	53	16.7	GU W1830	Fw	Calibration
Sappi	B3a	2010/04/16	2018/08/21	8.35	39	18.3	GU W1700	Fw	Calibration
Mondi Forest	B003	2011/07/04	2018/08/22	7.13	45	17.1	GGRAURO	Fw1210	Calibration
Mondi Forest	J006	2010/07/01	2018/08/21	8.14	43	22.8	GGRAURO	Hu2200	Calibration
Mondi Forest	B032	2012/08/01	2018/08/22	6.06	29	16.1	GGRAURO	Cv21	Calibration
Sappi	C15a	2010/06/16	2018/08/17	8.17	59	16.8	GU W1700	Fw	Calibration
Sappi	F7	2010/11/16	2018/08/14	7.74	54	21.2	GU W1830	Fw	Calibration
Sappi	G22b	2008/04/15	2018/08/10	10.32	20	15.8	GU W1022	Fw	Calibration
Sappi	G33b	2011/03/16	2018/08/10	7.40	20	19.2	GU W1022	Fw	Calibration
Mondi Forest	A017	2011/07/01	2018/08/11	7.11	32	27.8	GGRAURO	Vf2110	Calibration
Mondi Forest	B044	2011/06/01	2018/08/21	7.22	55	25.9	GGRAURO	Hu2100	Calibration
Mondi Forest	F011A	2012/08/02	2018/08/11	6.03	63	28.8	GGRAURO	Ct2100	Calibration
Sappi	B35b	2012/04/16	2018/08/17	6.34	60	20.2	GU SGU1932	Fw	Calibration
Sappi	B38	2011/03/16	2018/08/17	7.42	62	20.0	GU W1830	Fw	Calibration
Sappi	C55	2010/06/16	2018/08/20	8.18	41	22.9	GU SGU1932	Fw	Calibration
Sappi	D13b	2011/05/16	2018/08/07	7.23	63	15.1	GU W1830	Fw	Calibration
Sappi	E23f	2012/06/16	2018/08/07	6.14	44	14.0	GU W1700	Fw	Calibration
Sappi	E24g	2008/03/15	2018/08/07	10.39	44	14.4	MIXED	Fw	Calibration
Sappi	E4b	2010/07/19	2017/07/19	7.70	58.2	13.7	GU W1700	Fw	Validation
Sappi	E4c	2010/07/19	2017/07/19	7.70	54.5	12.9	GU W1830	Fw	Validation
Sappi	E4i	2010/07/19	2017/07/19	7.70	56.2	12.7	GU W962	Fw	Validation
Mondi Forest	F011A	2010/05/10	2018/04/12	7.92	84.1	21.0	GGRAURO	Hu2200	Validation
Mondi Forest	C002	2013/05/09	2018/04/18	4.92	55.1	17.8	GGRAURO	Hu26	Validation
Mondi Forest	D006	2011/04/21	2018/03/10	6.92	40.0	19.6	GGRAURO	Fw11	Validation
Sappi	A18	2008/08/15	2017/09/25	9.70	37.8	14.8	GU W1605	Fw	Validation
Sappi	A21a	2010/07/21	2017/07/25	7.70	39.1	14.4	GU SGU1932	Fw	Validation
Sappi	A21b	2010/07/21	2017/07/25	7.70	41.2	13.4	GU W1700	Fw	Validation
Sappi	A21i	2010/07/21	2017/07/25	7.70	41.0	13.7	GU W962	Fw	Validation
Mondi Forest	B060	2012/04/10	2018/03/15	5.92	60.3	19.7	GGRAURO	Fw1110	Validation
Mondi Forest	C001	2012/05/09	218/03/15	5.83	57.7	16.5	GGRAURO	Fw1110	Validation
Sappi	L11b	2010/07/20	2010/07/21	7.70	89.1	15.0	GU W1700	Fw	Validation
Sappi	L11e	2010/07/20	2010/07/21	7.70	92.7	12.6	GU A380	Fw	Validation
Sappi	L11j	2010/07/20	2010/07/21	7.70	93.5	13.1	GU W1013	Fw	Validation

Ct - Constantia form, Cv – Clovelly form, Fw – Fernwood from, Hu – Hutton, Vf – Vilafontes form.

Mean height was calculated by substituting quadatic mean diameter into Equation 1. Stand basal area (BA, m^2ha^{-1}) was estimated using Equation 3, and stand volume (V, m^3ha^{-1}) using an estimator by Burkhart and Tomé (2012) (Equation 4). Where V is the utilizable volume (m^3ha^{-1}), BA is the basal area (m^2ha^{-1}), Dq is the quadratic mean DBH (cm), DBH is the stem diameter at breast height (cm), n is the number of observed trees per plot, TPH is the number of stems (trees/ha), $Hmean$ is the mean height (m), and f the species-specific form factor.

$$Dq = \sqrt{\frac{\sum DBH^2}{n}} \quad (2)$$

$$BA = \frac{\pi * (Dq)^2 * TPH)}{40000} \quad (3)$$

$$V = BA * H_{mean} * f \quad (4)$$

Soil data

At the centre of each of the calibration sites, soil samples were collected from pits using a 1.2m manual steel auger at 10 cm intervals, until a soil depth of 1.2m was reached. Soil textural and chemical analysis was performed at the Institute for Commercial Forest Research (ICFR)

(Table 2). Soil class was then determined based on sand, silt, and clay content. Soil class was relatively homogenous, as expected in this region. Available Soil Water (ASW) was estimated from the soil textural properties, using the soil water characteristics equation by Saxton and Rawls (2006). Maximum ASW was calculated as the product of soil depth and derived available water capacity. In 3PG, the minimum available soil water (MinASW), which is used to account for water table access, is typically set to zero by default. However, if it is known that the plants have access to a deep permanent water source, this value can be set higher than zero. As a result, MinASW at five sites planted near perennial watercourses were increased to half of their ASW.

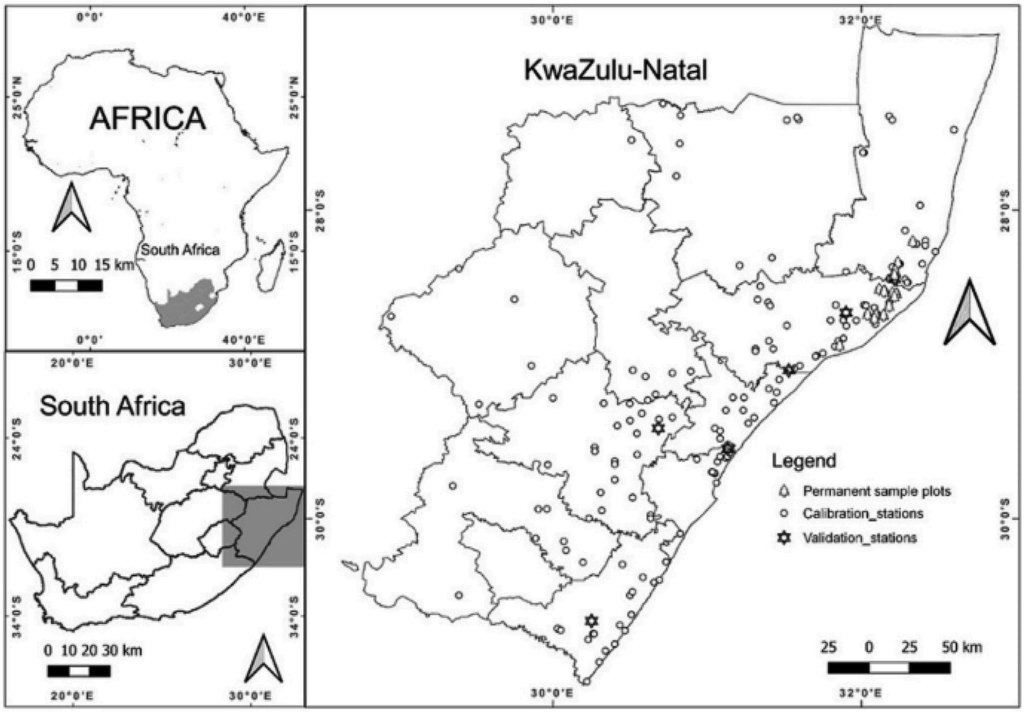

Figure 2: Map displaying weather station locations across KwaZulu-Natal province.

Table 2: Average soil textural and chemical properties across the soil depths of the calibration sites.

Compartment name	Silt (%)	Clay (%)	Sand (%)	Soil class	SOC (%)	N (%)	S (%)	P (%)	pH (%)	C:N (%)
E6a	0.03	0.04	0.93	Sandy	1.82	0.1	0.02	10.47	6.4	54.6
B3a	0.06	0.05	0.89	Sandy	3.07	0.13	0.03	3.26	4.9	71.2
B003	0.06	0.08	0.85	Sandy	1.19	0.08	0.02	15.4	5.9	44.7
J006	0.04	0.08	0.87	Sandy	1.39	0.09	0.02	33.87	6.7	43.6
B032	0.10	0.12	0.78	Loamy Sand	0.79	0.05	0.02	10.61	5.7	44.9
C15a	0.04	0.04	0.92	Sandy	1.41	0.07	0.02	3.79	4.8	61.5
F7	0.04	0.06	0.91	Sandy	0.72	0.04	0.01	2.88	5.4	56.9
G22b	0.04	0.04	0.92	Sandy	0.58	0.03	0.01	3.72	4.9	63.9
G33b	0.09	0.06	0.85	Sandy	1.01	0.07	0.02	3.08	5.3	42
A017	0.04	0.07	0.89	Sandy	1.54	0.09	0.03	4.2	5.3	52.4
B044	0.04	0.06	0.89	Sandy	1.22	0.1	0.03	4.48	4.9	33.7
F011A	0.03	0.06	0.92	Sandy	1.27	0.07	0.02	4.17	4.7	53.1
B35b	0.02	0.03	0.95	Sandy	0.73	0.05	0.02	3.99	5.5	46.6
B38	0.04	0.04	0.92	Sandy	0.89	0.05	0.02	4.97	5.7	54.4
C55	0.03	0.07	0.91	Sandy	1.28	0.09	0.03	4.98	5.2	42
D13b	0.02	0.04	0.94	Sandy	1.08	0.07	0.02	21.42	5.9	39
E23f	0.03	0.04	0.93	Sandy	1.12	0.07	0.02	6.23	6.3	47.2
E24g	0.05	0.10	0.84	Sandy	1.16	0.07	0.02	24.62	5.8	48.9

SOC: soil organic carbon, N: Nitrogen, S: Sulphur, P: Potassium, C:N – Carbon to Nitrogen ratio.

Fertility Rating

The 3PG model utilizes a Fertility Rating index (FR) to establish a correlation between soil fertility and stand productivity. The FR index assigns a ranking to soil fertility, ranging from 0 (extreme nutritional limitation) to 1 (no nutritional limitation). Although the empirical nature of the FR index has faced criticism, the assignment of FR to a specific site remains a challenging task (Landsberg; Sands, 2011). In this study, we explored the likely variability in FR. We performed multiple 3PG model runs at 0.1 FR intervals to obtain the optimized values for each site (Supplementary material Fig. S1). Stepwise regression was performed using the optimized FR values as the independent variable. Soil physical and chemical properties, the total rainfall, ASW, and site index values were used as the explanatory variable (Table 3 for variables selected as the final model). The site index was the only explanatory variable that significantly contributed to the model ($p < 0.01$). Although the model from the stepwise regression gave a good R-squared, the relationship explained by the model was not statistically significant ($p > 0.05$). However, using only site index decreased the proportion of the explained variance ($R^2 = 0.36$, $p < 0.05$). Consequently, and given that the region is characterized by relatively homogenous soils, FR was set to a constant value of 0.5 to run the 3PG model at both calibration and validation stages.

Table 3: Variables selected in the stepwise regression. N – Nitrogen (%), S – Sulphur (%), P – Phosphorus (%), CN – Carbon-Nitrogen ratio, SI – Site Index.

Variables	Coefficients	Std. Error	t value	prob
Intercept	-0.677	0.526	-1.287	0.227
N	1.664	1.999	0.832	0.425
S	-5.198	9.005	-0.577	0.577
P	-0.006	0.004	-1.400	0.192
pH	0.093	0.066	1.405	0.190
CN	0.004	0.003	1.290	0.226
SI	0.020	0.006	3.275	0.008**
R-squared	0.635			
Residual SE	0.097			
p-value	0.066			

p < 0.001 '***', p < 0.01 '**', p < 0.05 '*'

Weather data

Estimates of meteorological data at the location of the study sites were generated by applying the Random Forest (RF) supervised learning algorithm developed by Breiman (2001), using the R package, *randomForest* (Liaw; Wiener, 2002). Long-term daily weather data such as maximum and minimum temperature, precipitation, and solar radiation were obtained from the South African Sugarcane Research Institute (SASRI) and the South African Weather Services (SAWS) from January 2008 to December 2018. From these two databases, a total of 155 weather stations (Figure 2) were seleted to develop the regression model. In addition to latitude and longitude, the covariables used for modelling were aspect, elevation, slope, and distance from the ocean. Aspect and slope were derived from the GISCOE 20m Digital Elevation Model raster data. The distance from the ocean was calculated from the polyline of the African continent.

For evaluating the performance of the developed RF model, a subset of 6 out of the total 155 weather stations (Figure 2) was selected as validation stations. The RF model was applied to predict rainfall for these stations from 2008 to 2018. The performance analysis focused solely on precipitation data, considering its inherent spatiotemporal variability, which poses challenges for interpolation. A pair-wise comparison of model-predicted and observed monthly precipitation data was performed. The following statistical errors and indices from the Agricultural and Meteorological software (AgriMetSoft, 2019) were used to compare the predicted and observed data; Root Mean Square Error (RMSE), Mean Bias Error (MBE), Willmott index of agreement (d), coefficient of determination (R^2), and Nash Sutcliffe model efficiency index (E) (Equation 5, 6, 7, 8 and 9). Where o_i is the observed values, p_i is the predicted values, o is the average observation value, and n is the number of observations.

$$RMSE - \sqrt{\frac{\sum_{i=1}^{n}(o_i - p_i)^2}{n}} \quad (5)$$

$$MBE - \frac{\sum_{i=1}^{n}(o_i - p_i)}{n} \quad (6)$$

$$d = 1 - \frac{\sum_{i=1}^{n}(o_i - p_i)^2}{\sum_{i=1}^{n}(| p_i - o | + | o_i - o |)^2} \quad (7)$$

$$R^2 - \left(\frac{n(\sum o_i p_i) - (\sum o_i)(\sum p_i)}{\sqrt{[n\sum o_i^2 - (\sum o_i)^2][n\sum p_i^2 - (\sum p_i)^2]}}\right)^2 \quad (8)$$

$$E = 1 - \frac{\sum_{i=1}^{n}(o_i - p_i)^2}{\sum_{i=1}^{n}(| o_i - o |)^2} \quad (9)$$

Calibration of 3PG model

Following the parameterization guidelines presented by several authors (Sands, 2004b; Esprey, 2006; Landsberg; Sands, 2011), a base parameter set developed for *E.grandis* x *E.urophylla* hybrids in a different region by Borges et al. (2012) were used where parameters could not be calibrated due to lack of suitable data or showed low sensitivity ratings. Generic parameters, assigned values based on analogy with other species, such as solar radiation to Photosynthetically Active Radiation (molPAR_MJ = 2.3 mol/MJ), were chosen from Sands; Landsberg (2002) as default parameters.

Allometric parameters for stem mass as a function of DBH

Biomass harvest data were measured from destructive samples taken in 2018 from the subset of five sites. Three trees representing the first quartile (Q1), third quartile (Q3), and the maximum in the diameter distribution were destructively harvested in each site. Measurements recorded were total height, DBH, aboveground biomass (stem wood, branch, and foliage). Parameters for the allometric (Equation 10) relationship between tree-level biomass (w_s, kg/tree) and DBH were then estimated as defined by Sands; Landsberg (2002). Where B is stem diameter at breast height, a_s is the coefficient, and n_s is the power in the allometric relationship.

$$w_s = a_s B^{n_s} \tag{10}$$

The allometric parameter from the 15 harvested trees was used to calculate the individual tree mass for each tree measured at the 18 sites. Average w_S and Dq were determined for each site. Combining these 18 pairs of w_s and Dq, a single stand-based allometric relationship representing all sites was developed. This estimation followed Esprey (2006) recommendation to upscale the parameter values to stand level for consistency with 3PG calculations.

Density-independent mortality coefficients

Some of the sites experienced mortality during the rotation. As a result, we fitted the parameter values for density-independent mortality. The Clutter and Jones mortality function (Equation 11) was used to estimate tree survival per year, then the data modelled was fitted using a Gaussian function with a non-zero asymptote (Landsberg; Sands, 2011). Where, γNx = 0.60 (mortality rate for matured trees), γNo = 1.01 (the seedling mortality rate), and $t\gamma N$ = 3.39 (age at which mortality has median value).

$$\gamma(t) = \gamma Nx + (\gamma Nx - \gamma No)e^{-(\ln 2)t/t\gamma N} \tag{11}$$

Parameter estimation for Zululand *E.grandis x E.urophylla*

Eight parameters (test parameters) (Table 4) were selected from the list of 3PG parameters (base parameters). These parameters were selected because they could not be calibrated from the data available in this study, and 3PG outputs have shown sensitivity to them (Almeida et al., 2004; Esprey et al., 2004; Forrester; Tang, 2016). Published parameter values for *E.grandis* x *E.urophylla* by Almeida et al. (2004) and Borges et al. (2012) were set as biologically plausible bounds (to give three test values: low, medium, high) in the estimation process. An algorithm was developed as part of an *R3PG_Parameter_Testing* pipeline using R software (R Core Team, 2021) to generate all the possible combinations of the test parameter values. The *R3PG* calibration simulations utilized seventeen of the eighteen calibration sites listed in Table 1. One site (G22) was excluded due to tree theft at an early age, and the provided inventory data were from the adjacent compartment.

No observed time-series data for the state variables (W_F, W_S, W_R and θ_S) were available for parameter estimation in this study. We simulated growth from planting date (at age 0) and the initial biomass pools were set using default values (W_F = 50%, W_S = 25%, and W_R = 25%) (Sands, 2010). Therefore, parameter estimation was based on quadratic mean DBH, quadratic mean height, and basal area as surrogates for stem biomass. Basal area was selected because it is a function of stocking. The leaf area index (LAI) is a surrogate for foliage biomass. Though we lacked observed ground-based time-series LAI data for this study, we still evaluated the biological plausibility of the parameter and resulting 3PG predicted LAI values by qualitatively comparing them to the Landsat 8 Collection 1 Tier 1 Normalized Difference Vegetation Index (NDVI) product. We used the 8-Day NDVI composite dataset retrieved from Google Earth Engine (GEE) environment. The complete scripts and the template file for this algorithm are available on GitHub at https://github.com/EucXylo/R3PG_parameter_testing.

Selecting the optimized parameter set (pset)

All candidate psets generated were evaluated by matching their predicted Dq, Hmean, and BA values to corresponding observed data. To determine the best performing pset, a modified RMSE was used to account also for slope effects as defined in Equation 12. Where n is the number of observed values, SSE is the sum of square error, SSF is the sum of square fit (Figure 3).

$$eRMSE = \sqrt{\frac{SSE + SSF}{2n}} \tag{12}$$

Validation evaluation of 3PG performance

The predictive accuracy of the 3PG model was further tested by validating the model against data from 15 independent sites in the same region. Stand growth data at a specific age (ranging from 4 – 9 years) were made available. Summary of the site and stand information used is presented in Table 1. Weather data were obtained using the interpolation technique described. Plant available soil water was estimated from the South African soil classification map. However, ASW obtained from this map were overestimated (99 – 105mm) for sandy soil compared to the typical value (±80mm) for the region's soil form specified by Olivier (2017) and those derived from soil texture (34.7 – 60.7mm) used in model calibration. For this reason, the initial ASW was set as the mean ASW of the calibration sites. The optimized parameter set selected and three other Brazilian parameter sets by Borges et al. (2012) and Almeida et al. (2004) were used to run the 3PG model.

Table 4: Test parameters and their values set as bound during parameter estimation.

Parameter	*E.grandis* x *E.urophylla* (Borges et al., 2012)	Clone 15 (Almeida, Landsberg & Sands, 2004)	Clone 22 (Almeida, Landsberg & Sands, 2004)	*E.grandis* (Esprey, 2005)
pFS2	1.64	0.7	0.7	-
pFS20	0.15	0.1	0.11	-
pRx	0.5	0.6	0.6	-
Tmin	8	8	8	3
Topt	25	25	25	23
Tmax	40	36	36	25
wSx1000	300	180	180	-
CoeffCond	0.0324	0.045	0.05	-

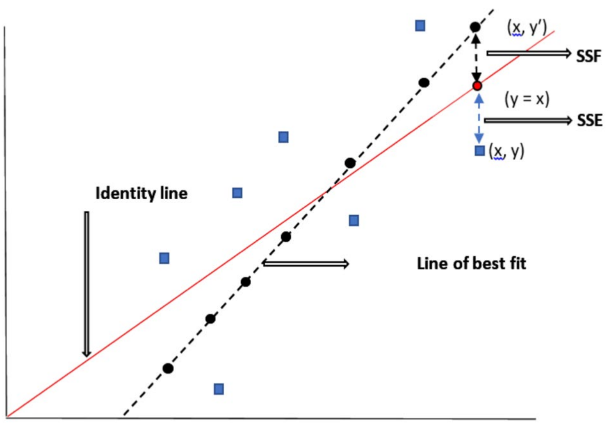

Figure 3: A hypothetical graph explaining the eRMSE concept. Where SSE is the sum of square error (R3PG-predicted vs. observed values); SSF is the sum of square fit error (line of best fit prediction vs observed values); solid red line identity line; black dashed line is the line of best fit; blue squares are the R3PG-predicted vs. observed values data; black circles are the regression fit values; red circle represents a perfect model.

Using these parameter sets, four sets of model predicted mean height and basal area were obtained and used to estimate stand volume using Equation 4; and these were compared with observed stand volume. The following statistical error and indices from AgriMetSoft (2019) were used to evaluate the performance of the 3PG model: Root mean square error (RMSE), coefficient of determination (R^2), and Nash Sutcliffe efficiency index (E).

Simulation software

For this study, simulation runs and optimization were performed using the 3PG package developed by Trotsiuk et al. (2020) in the R system for statistical computing (R Core Team, 2021). The package offers users a flexible switch between various options and submodules to use the original 3PGpjs (Landsberg; Waring, 1997) and 3PGmix (Forrester; Tang, 2016). To run the original 3PGpjs, we used *settings = list(light_model = 1, transp_model = 1, phys_model = 1, height_model = 1, correct_bias = 0, calculate_d13c = 0)*. The function *run_3PG* was designed for *SingleSite* run type. As a result, we developed a for-loop function to run *R3PG* for *MultiSite* run type.

RESULTS

Interpolated precipitation data

The average annual rainfall variation for all study sites from 2008 – 2018 was compared to the long-term mean rainfall (1959 – 1999) (Figure 4). It is worth noting the exceptionally dry years of 2014 and 2015, which marked the region's driest period on record. The very high dimensionless statistical indexes (> 0.80) used to evaluate the model's performance demonstrated a strong agreement between the observed and predicted precipitation data (Figure 4). RF model-predicted rainfall closely matches observed rainfall for the study period (2008 - 2018) (Table 2). This indicates that the RF model has been adequately calibrated to generate reliable rainfall predictions across the range of measured precipitation. In terms of prediction errors, the RF model exhibited lower errors (Figure 5). Nonetheless, there were indications of bias caused by the model's underestimation at the Oribi-flat Minnehaha weather station for a particular month (the square symbol in Figure 5). Given the excellent performance of the RF model, it was used to generate high-resolution weather data for growth modelling in this study.

Allometric parameters a_s and n_s

The biomass equations, with a_s = 0.099 and n_s = 2.51, fitted the data well (R^2 = 0.99; $p < 0.001$) (Figure 6). The standard errors for this parameter calibration are a_s = 0.477 and n_s = 0.005.

Parameter estimation

The parameter set with the lowest *eRMSE* was selected as the optimized parameter values for *E.grandis* x *E.urophylla* in the coastal Zululand region of South Africa. The list of parameter values for this study and Brazilian clones are presented in Table 5. Utilizing this parameter set enabled accurate predictions of mean height, basal area, quadratic diameter and stand volume during the calibration phase. The

3PG predictions explained over 80% of the variance for all output variables across the 17 calibration sites (Figure 7). The linear regression for all output variables were significantly different from zero ($p < 0.001$) (Figure 7). There was a low negative average bias for the output variables considered (-0.17 to -1.64), except for stand volume (-5.99) (Figure 7). This is as result of the model underprediction in most sites (Figure 7). The Nash Sutcliffe model efficiency index (E) indicated a strong match between 3PG prediction and observed data (E > 0.70, where E = 1 indicates a perfect match) (Figure 7).

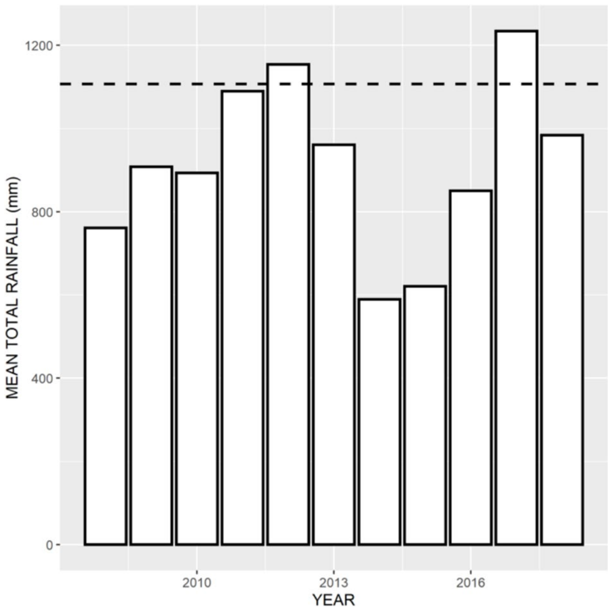

Figure 4: Mean annual rainfall for study sites (2008 – 2018) predicted by the Random Forest model. The black dash line indicates the long-term mean rainfall.

At the validation stage, the model-predicted basal area and mean height were used to estimate stand volume using Equation 4. All four parameter sets accounted for more than 60% of the variance in the observed stand volume (Figure 8), but the two parameter sets from Almeida et al. (2004) significantly undestimated fast-growing sites (Figure 8). The parameter set developed by Borges et al. (2012) has slightly greater precision (R^2 = 0.68) compared to this study (R^2 = 0.65) but it showed poor performance in terms of slope (Figure 8). The low modelling efficiency index observed with the optimized parameters derived in this study was due to the overprediction by the 3PG model (Figure 8). Overall, the optimized parameter set accurately reproduced the time-course growth pattern of the *E.grandis* x *E.urophylla* hybrids growing in the coastal Zululand region (Figures 9 and 10).

We observed realistic 3PG predicted LAI at some sites, particularly in the Northern (dry) region (E6a, B3a, B003, B032, and C15a). However, it is worth noting that within the Southern (wet) region, some sites (A017, B044, B35b, B38, C55, J006) exhibited remarkably high peak LAI values. The qualitatitive analysis of the predicted LAI in relation to the Landsat 8 NDVI values indicated a general decline in the NDVI values throughout the drought period from 2014 to 2015 (Figure 11).

DISCUSSION

This study findings suggest that 3PG model can be calibrated by estimating key parameters from a published parameter set developed in a different region. This aligns with the work of Fontes et al. (2006), where they calibrated the 3PG model for Portuguese eucalypt plantations using parameter set developed in Austrialia by Sands and Landsberg (2002). The coefficient (a_S) in the allometric relationship between tree-level biomass and DBH was higher (0.099) compared to values obtained by Almeida et al. (2004) and Borges et al.

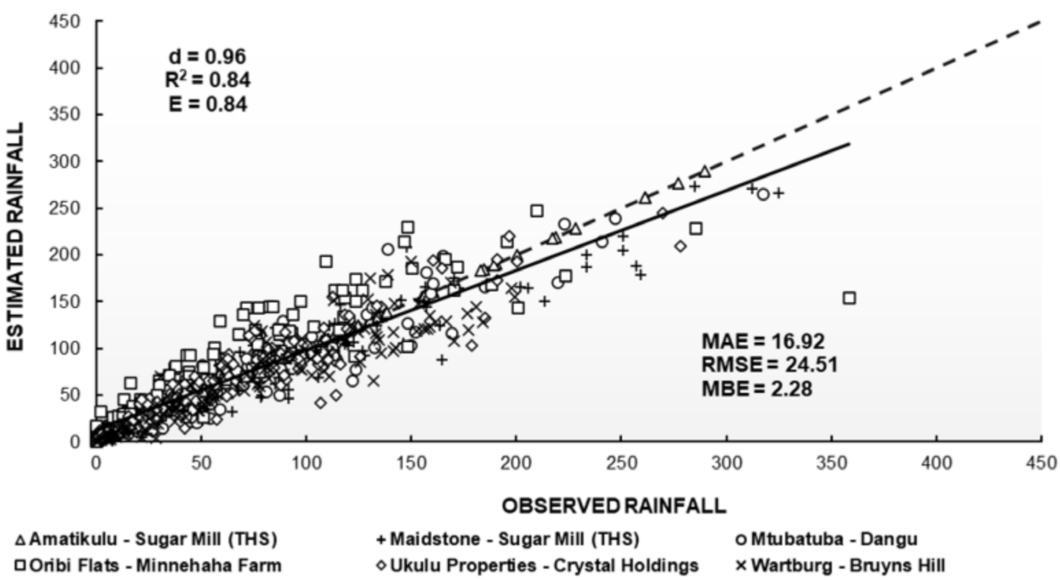

Figure 5: Comparison of observed and model-predicted monthly rainfall for six validation stations using the Random Forest model. Shapes represent weather stations.

(2012), while the power (n_S) in the allometric relationship fell within the range of values reported by both authors. These parameters play a crucial role in predicting stem diameter and basal area using the 3PG model.

Of the eight parameters estimated in this study, two parameters differed from the reported Brazilian clone values used as references: biomass partitioning between the foliage and stem (*pFS2*) and the minimum temperature (*Tmin*). The optimum temperature (Topt) matched the value obtained by Esprey (2006), while the maximum fraction of NPP allocated to the roots (pRx) match those obtained by Almeida et al. (2004). The soil water modifier (SWconst and SWpower) were different from the Brazilian parameters due to the soil type, while the remaining parameters matched values obtained by Borges et al. (2012).

Overall, the good agreement between the observed and predicted output variables (Figure 6) indicates adequate calibration of the 3PG parameters to predict forest growth in the study area. Furthermore, the *eRMSE* method demonstrated its ability to select optimized parameter with minimal residuals, low bias and a close alignment to the identity line (Figure 6). However, the 3PG model's accuracy in simulating the four output variables considered during the calibration was lower than Borges et al. (2012) for *E.grandis* x *E.urophylla*, with BA (R^2 = 0.98), Dq (R^2 = 0.97), Hmean (R^2 = 0.95), and stand volume (R^2 = 0.92). Similarly, Almeida et al. (2004) reported R^2 = 0.96 for BA, R^2 = 0.98 for Dq, and R^2 = 0.98 for stand volume. In contrast, for ***Eucalyptus grandis*** in South Africa, Esprey (2006) reported R^2 = 0.68 for Dq and R^2 = 0.69 for Hmean which are lower than the one obtained in this study.

The 3PG model underpredicted early growth from age zero to about five years at certain sites during the calibration phase (Figures 8 and 9). According to Landsberg and Waring (1997), these systematic errors are expected due to the limitation of using Beer's law to calculate absorbed photosynthetically active radiation. The model assumes a closed canopy which is not always true for young eucalypt plantations. In this study, some sites experienced mortality at post-planting, resulting in increased canopy gaps. This explains the bias reported in Figure 6. However, as the stand age, 3PG prediction tends to match with the observed values (Figures 8 and 9). This pattern was also observed by Esprey (2006) and Miehle et al. (2009).

During the validation phase, the performance of the 3PG model indicated its capacity to forecast stand growth across a wide range of sites which were not previously calibrated. The optimized parameter set provided a reasonble prediction of the observed stand volume. However, the model tended to overpredict in most sites (Figure 7), possibly due to uniform values of ASW and FR used across the validation sites. Due to the lack of detailed information on soil properties at the validation sites, we used the mean ASW from the calibration sites. The weak correlation between FR and soil nutrients observed during the examination of FR variation across the sites can be attributed to the high leachabilty of nutrients from the well-drained, coarse-textured soils present in this region (Dye et al., 2004). This emphasizes on the significance of a high-quality soil profile map for this region to obtain accurate soil information for tree growth modelling.

The 3PG model demonstrated its utility in identifying and quantifying the effects of the environmental factors affecting tree growth. This was illustrated using the 2014 – 2015 dry period (Figures 8 and 9). During the observed period, a noticeable decline in the growth rate of trees occurred across the majority of sites. However, we found that specific locations A017, B044, F011A, B35b, and C55 exhibited continuous growth even admist the dry period. It is important to emphasize that the decline in the Landsat 8 NDVI and 3PG predicted LAI values indicates an overall reduction in vegetation vigor (Figures 10). Nevertheless, the rate of decline and subsequent recovery varies across the different regions. These findings are consistent with the conclusions of Xulu et al. (2018), who also noted that certain clones in central east region of KwaMbonambi showed stable NDVI values during the dry period, while others declined. Visually inspecting these sites from satellite imagery shows they were established adjacent to indigenous forest conservation zones, which almost invariably grow along perennial watercourses. Accordingly, it would seem very likely that these plots had higher-than-normal access to groundwater. As a result, we increased the minimum available soil water (MinASW), which indicates access to the water table, and the 3PG model effectively simulated the observed continuous growth in these sites.

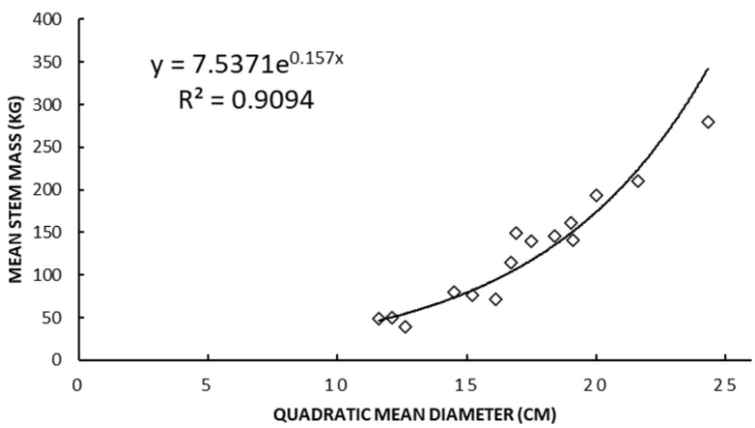

Figure 6: Allometric relationship between mean single-tree stem biomass (w_S) and Dq.

Table 5: List and source of parameters used in the calibration of 3PG, and the result of the 3PG calibration in this study.

Meaning/comments	Symbol	Units	***E.grandis x E.urophylla*** (Borges et al., 2012)	**Clone 15** (Almeida et al., 2004)	**Clone 22** (Almeida et al., 2004)	This Study	Source
Foliage:stem partitioning ratio @ D= 2cm	pFS2	-	1.64	0.7	0.7	1	E
Foliage:stem partitioning ratio @ D= 20cm	pFS20	-	0.15	0.1	0.11	0.15	E
Constant in the stem mass vs diam. Relationship	a_s	-	0.02	0.049	0.033	0.099	F
Power in the stem mass vs diam relationship	n_s	-	3.11	2.822	2.912	2.506	F
Maximum fraction of NPP to rootsFF	pRx	-	0.5	0.6	0.6	0.6	E
Minimum fraction of NPP to roots	pRn	-	0.1	0.07	0.12	0.1	E
Maximum litterfall rate	gammaF1	1/month	0.07	0.13	0.13	0.07	B
Litterfall rate at t = 0	gammaF0	1/month	0.001	0.00169	0.00169	0.001	B
Age at which litterfall rate has median value	tgammaF	Months	4	13	13	4	B
Average monthly root turnover rate	gammaR	1/month	0.025	0.025	0.025	0.025	B
Minimum temperature for growth	Tmin	°C	8	8	8	5	E
Optimum temperature for growth	Topt	°C	25	25	25	23	E
Maximum temperature for growth	Tmax	°C	40	36	36	40	E
Moisture ratio deficit for f_θ = 0.5	SWconst	-	0.5	0.5	0.5	0.7	D
Power of moisture ratio deficit	SWpower	-	5	5	5	9	D
Value of ‘m’ when FR = 0	m0	-	0	0	0	0	D
Value of ‘fNutr’ when FR = 0	fN0	-	0.5	0.6	0.6	0.6	D
Power of (1-FR) in ‘fNutr’	fNn	-	1	1	1	1	D
Maximum stand age used in age modifier	MaxAge	Years	9	9	9	9	B
Power of relative age in function for fAge	nAge	-	4	4	4	4	D
Relative age to give fAge = 0.5	rAge	-	0.95	0.95	0.95	0.95	D
Mortality rate for large t	gammaNx	%/year	0	0	0	0.6	F
Seedling mortality rate (t = 0)	gammaN0	%/year	0	0	0	1.01	F
Age at which mortality rate has median value	tgammaN	Years	0	0	0	3.36	F
Shape of mortality response	ngammaN	-	1	1	1	1	F
Max. stem mass per tree @ 1000 trees/ha	wSx1000	Kg/tree	300	180	180	300	E
Specific leaf area at age 0	SLA0	m2/kg	13.74	11	9	13.74	B
Specific leaf area for mature leaves	SLA1	m2/kg	7.56	8	7.3	7.56	B
Age at which specific leaf area = (SLA0+SLA1/2)	tSLA	years	1.23	2.5	2.5	1.23	B
Extinction coefficient for absorption of PAR by canopy	K	-	0.5	0.5	0.5	0.5	D
Age at canopy cover	fullCanAge	years	2	2	2	2	D
Maximum proportion of rainfall evaporated from canopy	MaxIntcptn	-	0.15	0.15	0.15	0.15	D
LAI for maximum rainfall interception	LAImaxIntcptn	-	3.33	3	3	3	D
Alpha	alphaCx	molC/molPAR	0.08	0.068	0.068	0.08	E
Ratio NPP/GPP	Y	-	0.5	0.47	0.47	0.5	B
Maximum canopy conductance	MaxCond	m/s	0.02	0.02	0.022	0.02	D
LAI for maximum canopy conductance	LAIgcx	-	3.33	3	3	3.33	D
Defines stomatal response to VPD	CoeffCond	1/mBar	0.0324	0.045	0.05	0.0324	B
Canopy boundary layer conductance	BLcond	m/s	0.2	0.2	0.2	0.2	D
Branch and bark fraction at age 0	fracBB0	-	0.59	0.3	0.3	0.59	B
Branch and bark fraction for mature stands	fracBB1	-	0.19	0.12	0.12	0.19	B
Age at which fracBB = (fracBB0+fracBB1)/2	tBB	years	2.17	2	2	2.17	B
Minimum basic density for young trees	rhoMin	t/m^3	0.382	0.48	0.4	0.382	B
Maximum basic density for older trees	rhoMax	t/m^3	0.505	0.52	0.48	0.505	B
Age at which rho = (rhoMin+rhoMax)/2	tRho	years	2.264	3	3	2.264	B
Constant in stem height relationship	aH	-	0.67	0	0	0.67	B
Power of DBH in stem height relationship	nHB	-	1.27	0	0	1.27	B

Value source: B – base parameter (Borges et al., 2012), D – default (Sands & Landsberg, 2002), E – Estimated, F – fitted.

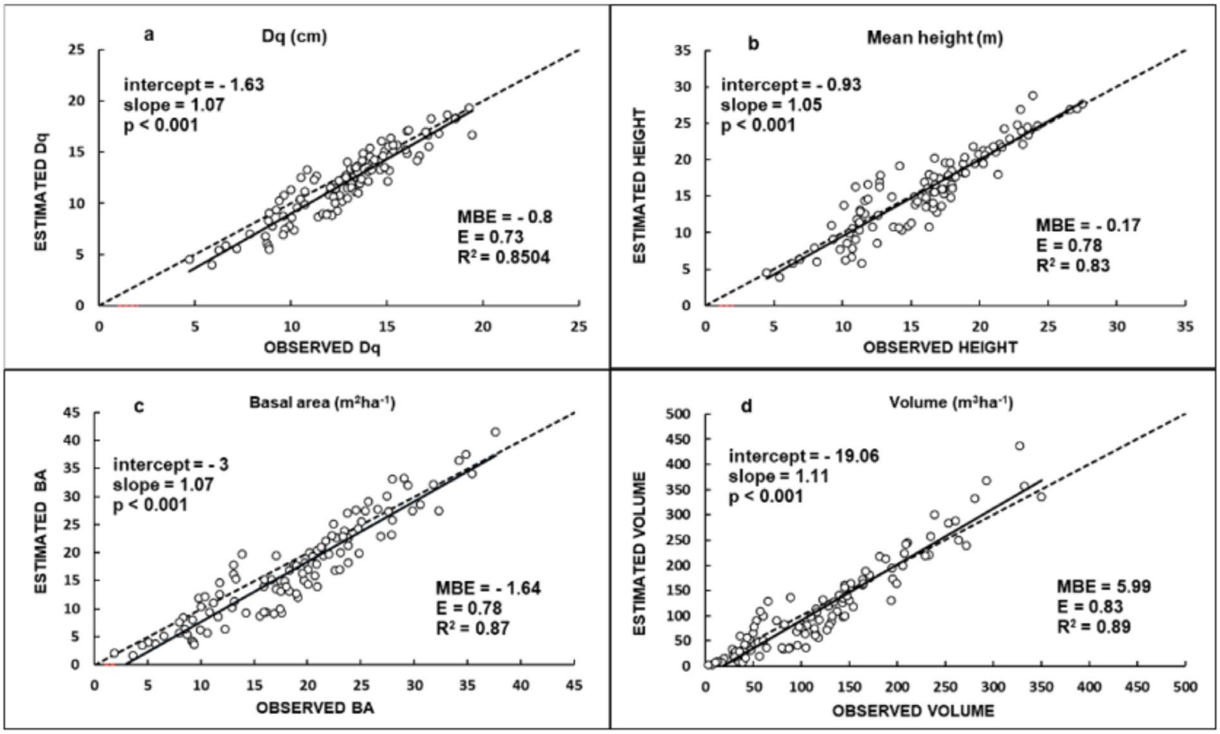

Figure 7: Statistics describing the relationship between observed and predicted variables at the calibration stage for (a) quadratic mean diameter (b) mean height (c) basal area, and (d) volume. Black dash lines are identity lines (1:1), solid black lines are fitted lines from the regression.

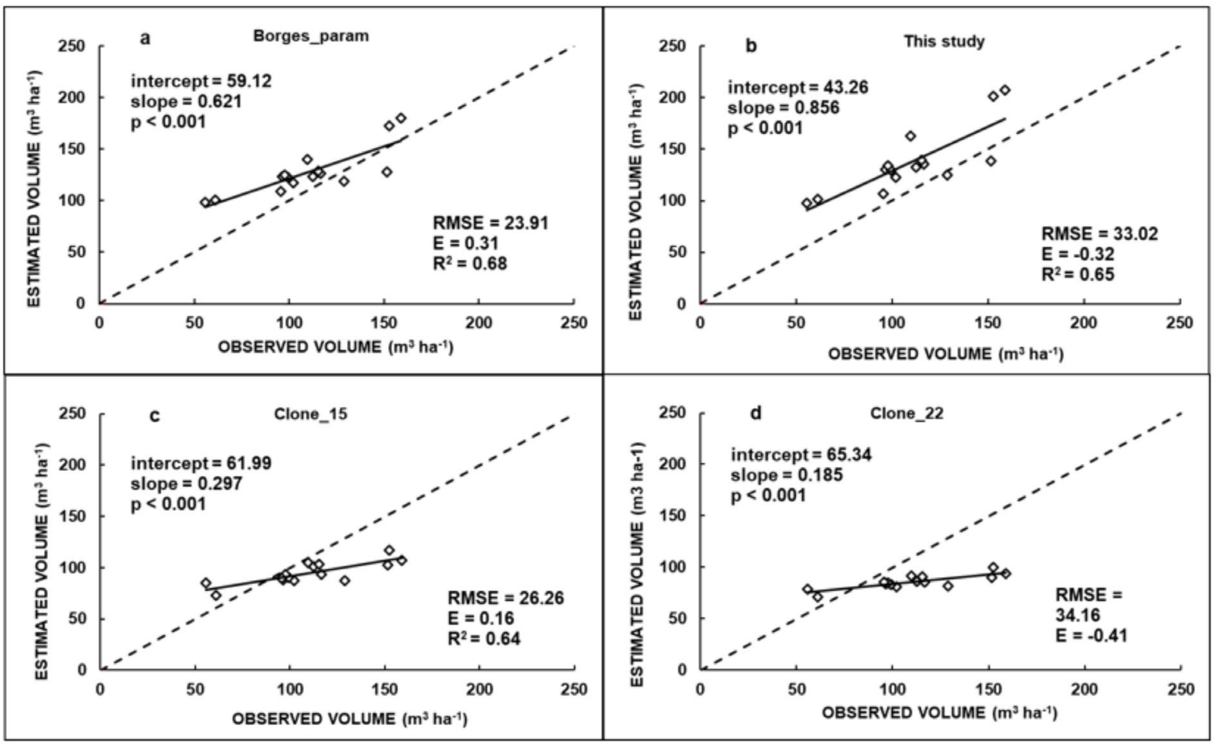

Figure 8: Statistics describing the relationship between observed and predicted stand volumes for the different parameter set (a) Borges et al. (2012), (b) This study, (c & d) Almeida et al. (2004) used at the validation sites. Black dash lines are identity lines (1:1), solid black lines are fitted from the regression equation.

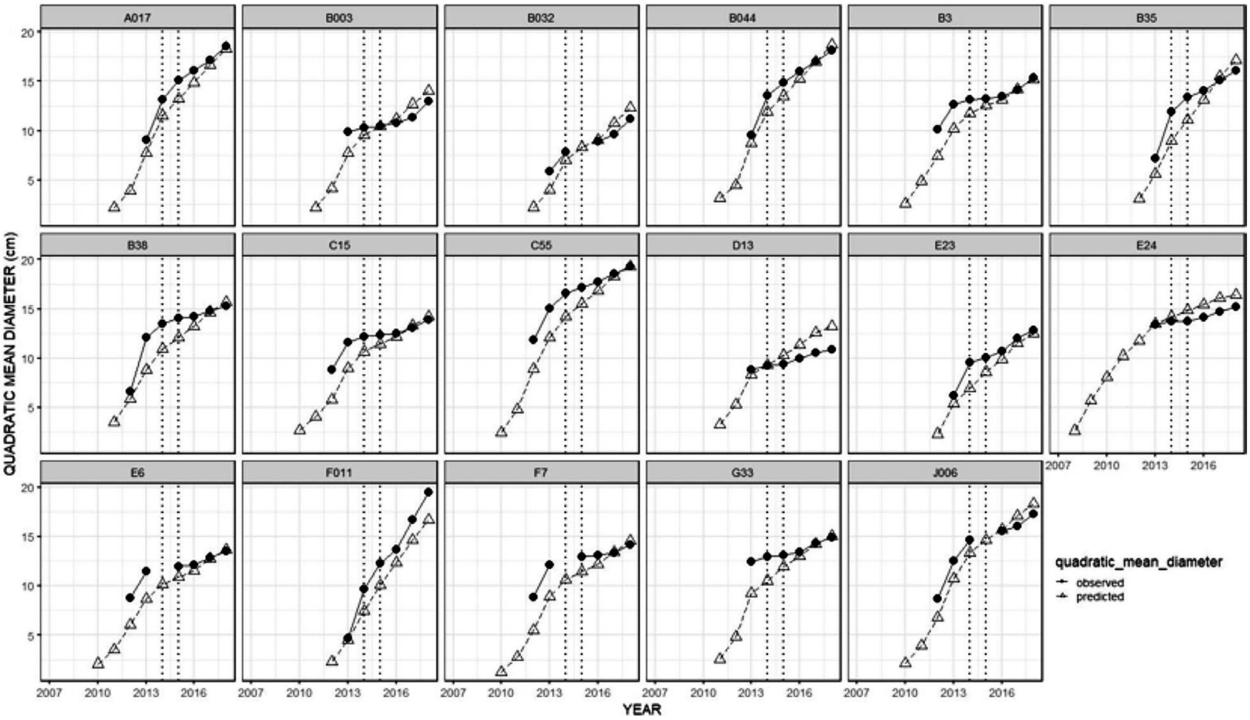

Figure 9: Comparison of observed (line with dark circles) and predicted (line with white triangles) time series quadratic mean diameter (cm) for the calibration plots. The two black vertical lines represent drought years (2014 – 2015).

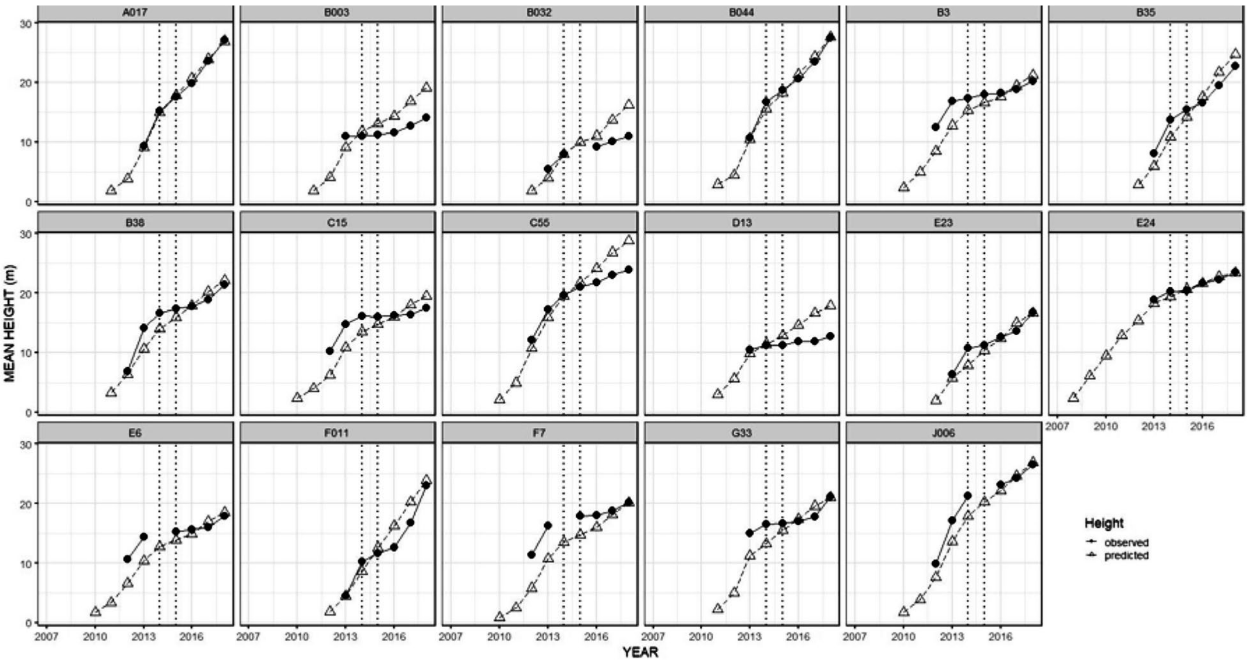

Figure 10: Comparison of observed (line with dark circles) and predicted (line with white triangles) time series mean height (cm) for the calibration plots. The two black vertical lines represent drought years (2014 – 2015).

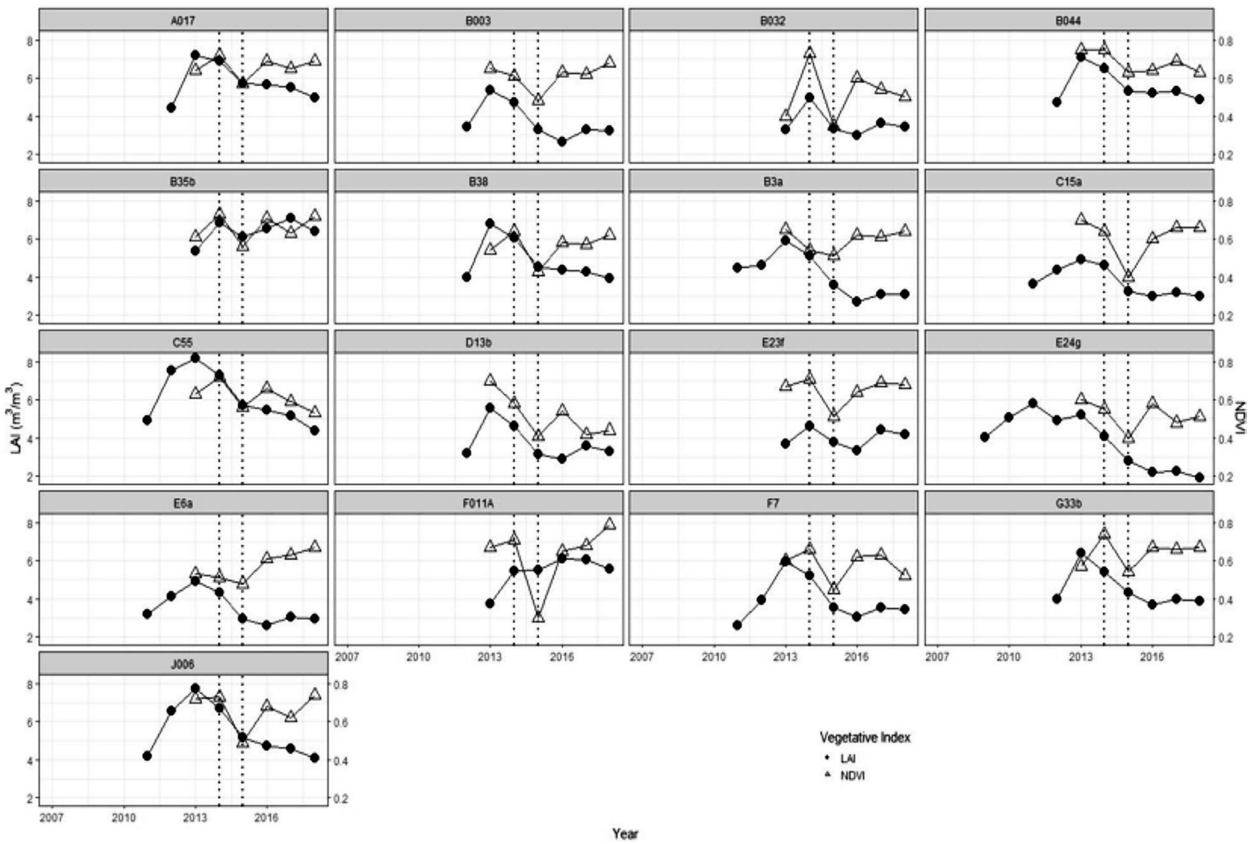

Figure 11: Comparison of 3PG predicted LAI values (line with dark circles) and Landsat 8 NDVI values (line with white triangles) across the 17 calibration sites. The two black vertical lines represent drought years (2014 – 2015).

The concurrence of these observations lends credibility to the biological plausibility of the 3PG model's predictions and supports its effectiveness in capturing changes in vegetation dynamics in response to fluctuating environmental conditions such as droughts.

CONCLUSIONS

The random forest regression model offers an accurate and reliable approach for estimating long-term weather data for ungauged sites, enabling their use in process-based modelling. The *R3PG* package facilitated model parameterization by integrating several algorithms with the 3PG model. The study concluded that the 3PG model could be calibrated using parameter set from a different region to characterize *Eucalyptus grandis x urophylla* hybrid stands in South Africa. The MinASW variable enables accurate simulation of sites with access to ground water. The overprediction of stand volumes observed during the validation stage was due to the lack of soil water information at the validation sites, emphasizing the neccesity for accurate soil information in this area. Overall, the 3PG model demonstrated its potential in providing realistic predictions of stand growth over time in response to environmental and management changes, as well as exploring scenarios (*"what if" questions*).

AUTHOR CONTRIBUTION

Project Idea: DMD

Database: IG

Processing: OFG; KCM; IG

Analysis: OFG; KCM

Writing: OFG

Review: KCM; IG; DMD

ACKNOWLEDGEMENTS

We express our sincere gratitude to Mondi South Africa and Sappi South Africa for providing the PSPs data and funding. We also appreciate the South African Sugarcane Research Institute (SASRI) and South African Weather Services (SAWS) for providing the weather data.

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