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Research Article

Dominant Height Model for Site Classification of *Eucalyptus grandis* Incorporating Climatic Variables

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This study tested the effects of inserting climatic variables in *Eucalyptus grandis* as covariables of a dominant height model, which for site index classification is usually related to age alone. Dominant height values ranging from 1 to 12 years of age located in the Southeast region of Brazil were used, as well as data from 19 automatic meteorological stations from the area. The Chapman-Richards model was chosen to represent dominant height as a function of age. To include the environmental variables a modifier was included in the asymptote of the model. The asymptote was chosen since this parameter is responsible for the maximum value which the dominant height can reach. Of the four environmental variables most responsible for database variation, the two with the highest correlation to the mean annual increment in dominant height (mean monthly precipitation and temperature) were selected to compose the asymptote modifier. Model validation showed a gain in precision of 33% (reduction of the standard error of estimate) when climatic variables were inserted in the model. Possible applications of the method include the estimation of site capacity in regions lacking any planting history, as well as updating forest inventory data based on past climate regimes.

1. Introduction

In its wider scope, forest management involves the choices of strategies that ensure the sustainability of the enterprise as a whole. The optimum management regime, under certain conditions of demand, productivity, distances, and silvicultural and harvests costs, is the higher objective procured. Thus, the choice of the ideal management practice for each forest site greatly contributes to the success of the activity.

According to Louw and Scholes [1], the classification of forest site productivity requires the knowledge of the geology, topography, climate, soils, and biotic factors that occur in the local. These authors sustain that the classification of forest sites should have ecological bases and not aligned specifically with productivity (even if a covariance occurs). Although the use of site factors that influence forest growth (e.g., soil characteristics, climatic conditions) for the classification of site quality is reliable to differentiate broad regions of growth, in forestry the use of more direct stand characteristics (e.g., volume, height) is more common due to practical reasons.

The use of height growth for assessing site quality in forest stands seems to have been first proposed by Remy de Perthuis de Laillevault, in the second half of the 18th century, working with coppice with standards stands in France [2]. According to Skovsgaard and Vanclay [3], site classification by stand height has become one of the most universal practices in forestry and is recognized as one of the most suitable indicators of site productivity for management purposes in even-aged forest stands.

Originally this type of classification was developed for slow growing species, sustaining cutting cycle ages that can reach up to hundreds of years [4–6]. Under these long rotations site classification has been reliable using only soil properties, stand density, and forest age. However, when the species under consideration are fast growing with shorter rotation ages, the stability of site classification is not always verified. *Eucalyptus* plantations in Brazil have very high productivity potential, with values of up to 83 m^3/ha/year being reported for sites that have completed a full rotation [7]. A common rotation age for *Eucalyptus* stands managed in Brazil for energy or pulp wood is of seven years [8]. With this short rotation, any change in climate, such as severe drought stress, has direct effects on productivity and wood quality [9].

A science that is under growing development and is linked to plant physiology is process-based modeling. Focusing on the knowledge to understand the causes of biological processes, this area of study has evolved considerable knowledge of the interaction between plant x soil x water x atmosphere, allowing for a generalized and physiologically based view to predict growing conditions. Owing to its complex nature, process-based models tend to be more research oriented, while empirical models more management oriented.

Process-based models give more general answers and have a greater capacity of prediction in situations outside the database used to parameterize the model, while empirical models are more objective, as long as the prediction in question is restricted to the database of its formulation [10, 11].

The approximation of the two modeling philosophies represents an important step towards a different modeling strategy, called hybrid models. Empirical and process approaches can be merged into hybrid models in which the shortcomings of both component approaches can be overcome to some extent [12].

Incorporating climatic variables into traditional biometric models facilitates the procedure's distribution and application [13]. The mentioned authors claim that this way the responses obtained from the models is one which forest managers are accustomed with. Such types of models have been applied with success in the estimation of site index of *Pinus patula* by Louw and Scholes [14] and for the projection of dominant height values of *Eucalyptus grandis* by Filho et al. [15].

The objective of this work is to propose an empirical biometric model for the prediction of site classification which considers climatic variables for *Eucalyptus grandis* plantations for cellulose production, this way improving the site estimates and permitting an estimate of productivity in areas without a history of forest plantations.

2. Material and Methods

2.1. Database. Inventory data from 1999 stands were used. The stands are located in southern Bahia State and Espírito Santo State, Brazil. The stands ages ranged from 1 to 12 years and consisted of the same genetic material. The initial planting density was of 1111 trees per hectare (3 × 3 m), with an average mortality of 7.6%. The dominant height per stand, which is the dependent variable used, was obtained as the mean dominant height (mean height of the 100 largest diameter trees per hectare) from each plot. The plots dominant height values were averaged for each stand; this way each stand/age pair consisted of one value of dominant height, regardless of the number of plots. The sampling intensity consisted of a minimum of 2 plots, a maximum of 75 plots, and a mean of 5.3 plots per stand. The use of the mean data from the stands contributed to a better representation of the site capacity here represented by the mean dominant height and also approximates to procedures used by forest companies to classify sites.

The climatic variables used in this study were obtained from 19 different climatic stations distributed in the study area, and their descriptive statistics can be seen in Table 1. The value of dynamic variables such as monthly precipitation, monthly potential evapotranspiration calculated from the Thornthwaite-Mather method, and temperature were calculated as the mean monthly values from the planting age to the inventory age. Some static variables were also used, such as latitude of the stand and soil properties (percentage of clay, silt, and sand). Table 1 shows the descriptive statistics of the database used, and Figure 1 shows the distribution of the observed dominant height per age.

The standard deviation of the mean monthly values (precipitation and potential evapotranspiration) was tested as dependent variables in order to verify whether irregular or regular climate regimes can help model the behavior of dominant height.

As shown in Figure 1, the distribution of dominant height values over the years presents a broad range of variance. The observed variation in dominant height at age 6, for example, was approximately 15 meters, which in turn implies in the range of different productive capacity of the stands achievable at age 6.

2.2. Paring of the Climatic and Inventory Variables. To associate each stand to a meteorological station, the geometric center of each stand was calculated using the Thiessen-polygon procedure, and the station closest to the stand's center was assigned to that particular stand.

Thus, for each observation of dominant height and age, a series of climatic data was related. Static variables such as soil texture and latitude were considered directly. Dynamic variables such as precipitation, water deficit, and evapotranspiration, among others, had their monthly means and deviations calculated from the plantation age of each stand up to the measurement date and were then associated with the dominant height and age.

2.3. Selection of the Variables and Modeling Development. When a data set is composed of many variables, the identification of which of them are most successful in identifying the variability in the system as a whole is a typical problem treated by multivariate statistics.

The data set of all the climatic variables was analyzed using Principal Components Analysis (PCA) technique, which returns the same number of components as the numbers of variables. Inside each component, a relative weight is assigned to each one of the tested variables, which serves as a basis for the identification of the variables that explains the most variability in the system with the least correlation amongst them, minimizing the effect of multicollinearity.

Table 1: Descriptive statistics of the database used to model dominant height in function of age with incorporation of climatic variables.

Variable	Descriptive statistics			
	Mean	Minimum	Maximum	CV[b]%
Stand				
Planting age (year)	1994.9	1987.0	2000.0	—
Dominant height (m)	20.9	4.9	37.3	19.0
Mean annual dominant height increment (m/year)	4.7	2.2	9.0	20.8
Age (years)	4.6	1.0	12.3	31.8
Environmental				
Latitude	19.1	17.6	19.9	3.3
Content of clay in the soil (%)	35.6	8.5	56.0	19.9
Content of silt in the soil (%)	7.0	5.5	8.3	6.7
Content of sand in the soil (%)	57.2	36.2	86.0	12.8
Maximum monthly temperature (°C)	28.4	26.1	30.5	3.1
Mean monthly temperature (°C)	23.8	21.3	25.1	2.5
Minimum monthly temperature (°C)	20.3	17.9	21.3	3.0
Monthly precipitation (mm)	94.5	63.0	188.0	12.7
Monthly precipitation—sdm[a] (mm)	11.7	6.9	43.3	30.7
Monthly potential evapotranspiration (mm)	103.8	75.6	120.5	7.1
Monthly potential evapotranspiration—sdm (mm)	4.1	2.3	7.1	18.3

[a]sdm: standard deviation of the mean monthly values, [b]CV: coefficient of variation.

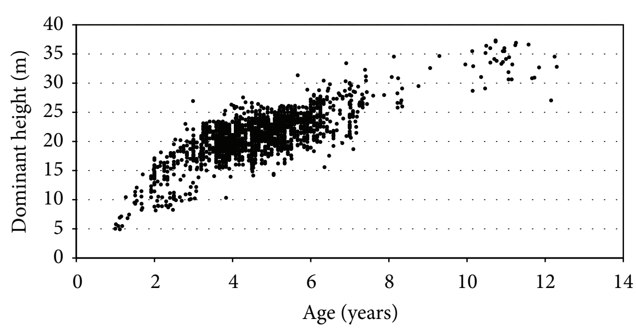


Figure 1: Distribution of the dominant height per age of the 1999 stands used.

This way, for each principal component, the variable which presented the highest coefficient was chosen and used for the modeling. Only components with eigenvalue greater than 1 were selected.

It is important to note that PCA is an exploratory technique used for the evaluation of the variability in a database [16] and is very robust as an auxiliary technique when used in combination with other statistical techniques, such as regression analyses [17]. Thus, PCA was used to detect which of the 11 environmental variables presented in Table 1 better represented the variability in the data set. The next step was to take the selected variables from the PCA and apply a correlation analysis with annual increment in dominant height, this way finding the variables which best explained the variation in dominant height.

2.4. Model for the Estimation of Site Index. Chapman and Richards applied a generalization of Bertalanffy's model, which is presented in model (1). Model (1) possesses the typical characteristics of a biological yield model, which are as follows: it begins at point zero; presents accelerated growth at yearly ages; presents an inflection point where the growth decelerates; and includes an asymptote which reflects the maximum value obtainable by the organism.

The productive capacity of a site is related to the asymptote value that an equation can obtain and is represented by the A coefficient of model (1). In order to model the effects of the climatic variables in dominant height growth, a modifier of the A coefficient was developed as shown in (2), and its inclusion in model (1) is shown in (3)

$$\text{Hdom} = A \cdot \left(1 - e^{\text{incl} \cdot t}\right)^{\text{inf}}, \quad (1)$$

$$\text{Modi}_A = c_1 \cdot \text{var}_1 + c_2 \cdot \text{var}_2 + \cdots, \quad (2)$$

$$\text{Hdom} = A \cdot \left(\text{Modi}_A\right) \cdot \left(1 - e^{\text{incl} \cdot t}\right)^{\text{inf}}, \quad (3)$$

where Hdom = dominant height at age t; t = age of the dominant height estimate; A, incl, and inf = asymptote, inclination, and inflection parameters; Modi_A = modifying factor of the asymptote; var_i = selected environmental variables; $c_1, c_2, \ldots$ = regression coefficients.

Using the asymptote modifier, site index curves that are commonly treated exclusively as a function of age also acquire a flexible behavior in relation to climatic conditions.

2.5. Model Validation and Application. According to Vanclay and Skovsgaard [18], the most convincing validation tests are those where a database independent of the one used to adjust the model is used to validate the model. Therefore, an entire region south of the study area (latitude 20°04′51″ south) was

TABLE 2: Weights of the first four principal components (eigenvalue greater than 1) from the PCA using the environmental data.

Variables	Components			
	1	2	3	4
Latitude	0.386	−0.596	−0.446	−0.342
Clay	0.567	−0.695	0.276	0.159
Silt	0.467	−0.446	0.283	0.334
Sand	−0.574	0.696	−0.290	−0.177
Maximum temperature	−0.612	−0.422	−0.480	−0.147
Mean temperature	**−0.843**	−0.384	0.283	−0.168
Minimum temperature	−0.526	0.093	**0.779**	0.061
Precipitation	0.438	0.136	0.296	**−0.722**
Precipitation—sdm	0.540	0.451	0.323	−0.498
PET	−0.822	−0.430	0.283	−0.179
PET—sdm	−0.058	**−0.729**	−0.032	−0.401
Total variance	3.54	2.79	1.63	1.30
Total variance %	32.21	25.40	14.82	11.82
Accumulated variance	3.54	6.34	7.97	9.27
Accumulated variance %	32.21	57.60	72.42	84.24

reserved for this purpose. The database used in the validation contained 40 stands. The sampling techniques and pairing of the climatic data were the same as in the database used to adjust the model.

The validation was performed with models (1) and (3), that is, with the inclusion or not of climatic variables. The standard error of estimate (SEE) was used to evaluate a possible gain in precision using climatic variables.

To test the model's behavior under extreme climatic data input values, dominant height estimates were obtained for age 7 (a typical reference age used for *Eucalyptus* site index classification in Brazil) using different ranges of temperature and precipitation. The tested climatic variables variation amplitude used was the mean plus/minus 3.5 standard deviations of the mean temperature and precipitation values presented in Table 1.

The final test of the methodology consisted in applying the model to generate site index curves for different climatic conditions. Six curves were generated considering 600 to 2100 mm of annual precipitation. This methodology was applied (using the modifier asymptote) for creating anamorphic curves, using the parameter prediction method. The mean monthly temperature was represented from a linear model constructed with precipitation as the independent variable.

3. Results

3.1. Analyses of the Environmental Variables in the Site Classification Model. Table 2 presents the weights of the first four principal components obtained in the PCA. Together, the first four principal components account for 84.24% of the variability in the data.

According to Table 2, the variables most important in explaining the variability in the database were mean temperature (mtemp); potential evapotranspiration—sdm (PET sdm); mean minimum temperature (mintemp); mean precipitation (mprec).

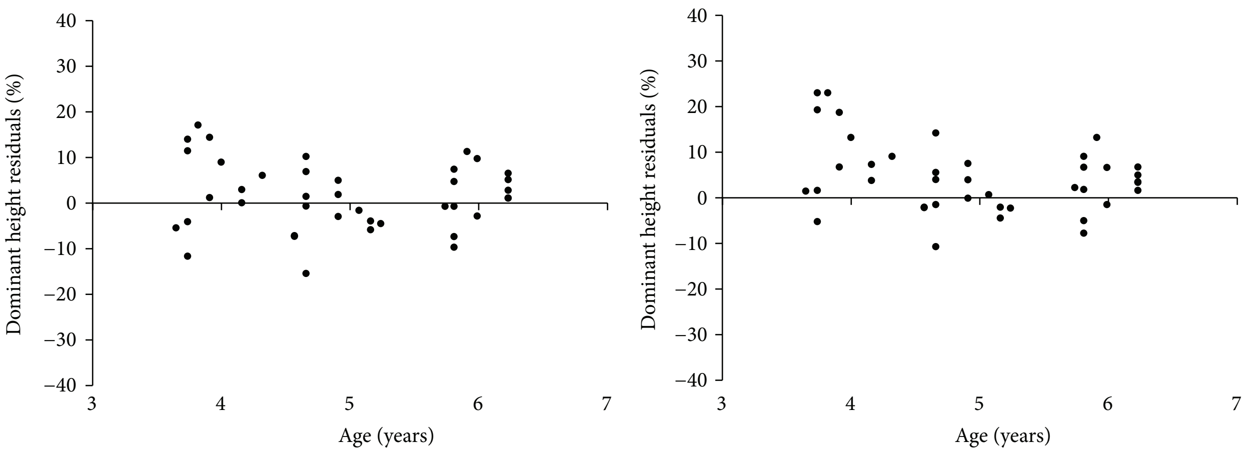
TABLE 3: Linear correlation analysis between mean annual dominant height increment and the variables selected in the Principal Components Analysis.

Variables	MAI dominant height
Mean temperature	−0.35
Potential evapotranspiration—sdm	−0.25
Mean minimum temperature	−0.17
Mean precipitation	0.27

Although these variables were responsible in explaining 84.24% of the variability of the database, this does not guarantee that they possess correlation with dominant height. A correlation matrix was elaborated using the variables selected in the PCA and mean annual dominant height increment, MAI (Table 3). The MAI was used in order to isolate the effect of age in the analysis. Only stands with ages between 5 and 8 years were used in this analysis, since this is the typical reference age range used in site classification, considering *E. grandis* plantations for cellulose production.

Table 3 shows that the correlation between mean annual dominant height increment and the selected climate variables is not strong. The variables mean temperature, potential evapotranspiration—sdm, and mean minimum temperature all had a reverse relationship with MAI dominant height. Only precipitation presented a positive correlation with MAI dominant height, indicating that the more water available for the plants the greater the growth.

Owing to difficulties of converging the nonlinear equation using the four variables, only the two variables with the highest correlation presented in Table 3 were included in the model, mean temperature and mean precipitation.



(a) (b)

Figure 2: Distribution of the residuals of the validation database for the dominant height models with (a) and without (b) climatic variables.

Table 4: Coefficient estimates and precision statistics for the adjusted dominant height equations with and without climatic variables.

Statistics	Without climatic variables	With climatic variables
Asymptote (A)	42.82011	50.01209
c_1 (mtemp)	—	0.014321
c_2 (mprec)	—	0.003096
Incl (inclination)	−0.09055	−0.1927
Inf (inflection)	0.675889	0.782733
R^2 (%)	67.9	72.2
Standard error of estimate (m)	2.32	2.16
Gain in precision of SEE (%)	—	6.9

Thus, the asymptote modifier presented in (2) assumed the structure shown as follows:

$$\text{Modi}_A = c_1 \cdot \text{mtemp} + c_2 \cdot \text{mprec}. \quad (4)$$

Table 4 shows the results of the two adjusted equations, the equation without climatic variables adjusted using model (1) and the equation considering climatic variables adjusted using model (3) and the asymptote modifier (4).

3.2. Model Validation and Application. To ensure that the adjusted models performed good outputs of dominant height in databases different from the one used for parameter estimation, both adjusted models from Table 4 were applied to an independent database; the precision statistics are presented in Table 5. The distribution of the residuals is shown in Figure 2. The residual distribution for the model with climatic variables was more stable than the model without climatic variables, especially at younger ages.

Table 6 shows dominant height projections at age seven using the model with climatic variables and varying climatic conditions. No biologically unreasonable value was observed in these estimates, even for the most extreme input values.

Table 5: Comparative statistics of the dominant height equations with and without climatic variables applied to the validation database.

Statistics	Dominant height model: Without climatic variables	Dominant height model: With climatic variables
Standard error of estimate (m)	4.34	2.89
Standard error of estimate (%)	19.38	12.83
Gain (%)	—	33.6
Mean residual (%)	4.42	1.46

The application of the model to generate site index classes based on different precipitation regimes is presented in Figure 3. The mean monthly temperature input values used in construct Figure 3 were obtained from the following linear equation: mean monthly temperature = 24.153 − 0.00324∗ mean monthly precipitation, which presented a coefficient of determination of 33% and a standard error of estimate of 0.59°C.

At age seven, the dominant height values presented in Figure 3 ranged from 19.7 to 34.8 m for the annual precipitations of 600 and 2100 mm, which represents a range of 15.1 m. Estimated site curves were well adhered to the observed values.

4. Discussion

The incorporation of climatic variables in the dominant height model allowed for better estimates. According to Table 4, when compared to the equation without climatic variables, an increase of 4.3% was obtained in the coefficient of determination and a reduction of 0.16 m was obtained in the standard error of estimate with the inclusion of climatic variables in the model. This translates to a gain in precision of 6.9%. Snowdon et al. [13] obtained similar values of precision gain using Schumacher's model to estimate height in a *Pinus radiata* spacing experiment. Inserting climatic

Table 6: Dominant height estimates at age seven considering different conditions of mean monthly precipitation and mean monthly temperature.

Number of sd	Number of sd[a]	Mean monthly precipitation (mm)							
		−3.5	−2.5	−1.5	0	1.5	2.5	3.5	6
	Mean monthly temperature	52	64	76	95	113	125	137	167
−3.5	**21.9**	18.7	20.2	21.7	24.0	26.2	27.7	29.1	32.8
−2.5	**22.4**	19.1	20.5	22.0	24.3	26.5	28.0	29.5	33.1
−1.5	**23.0**	19.4	20.9	22.3	24.7	26.9	28.3	29.8	33.5
0	**23.9**	19.9	21.4	22.8	25.2	27.4	28.8	30.3	34.0
1.5	**24.8**	20.4	21.8	23.3	25.6	27.8	29.3	30.8	34.5
2.5	**25.3**	20.7	22.2	23.6	26.0	28.2	29.6	31.1	34.8
3.5	**25.9**	21.0	22.5	24.0	26.3	28.5	30.0	31.4	35.1

[a]sd: standard deviation.

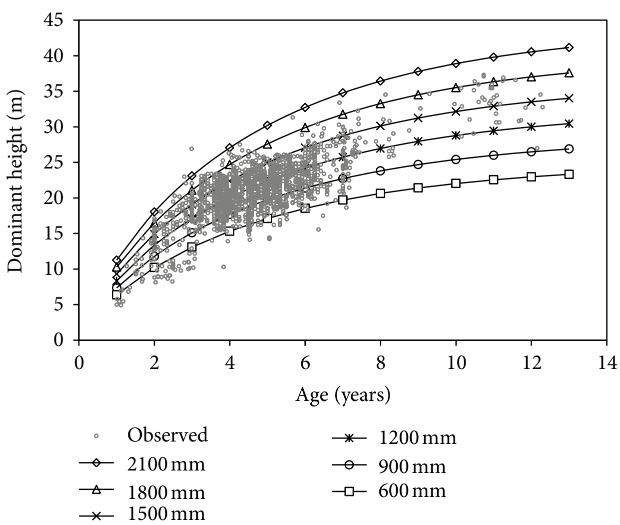


Figure 3: Dominant height curves in function of annual precipitation using model (3) and the adjusted parameters in Table 4.

As for the application of the model in an independent database, the inclusion of mean monthly temperature and precipitation in the model resulted in better estimates of dominant height, when compared to the equation without climatic variables. The standard error of estimate was reduced by 33.6%, and the mean residual went from 4.42% to 1.26%, demonstrating that the residuals of the estimates presented less tendencies.

Site quality classification using age and dominant height provides a convenient and consistent evaluation method of site quality, since all environmental factors are reflected interactively in height growth, which is also related to volume. However, specific environmental conditions such as above average rainfall or temperature variations in a particular year give rise to abnormal increase in height which traditional models (which do not use climatic variables) are not able to explain. Thus, the proposed methodology can provide greater accuracy in dominant height (and consequentially volume) estimates for short rotation forests, since they are potentially more sensitive to fluctuation of the climatic regime than long rotation forestry.

variables obtained from the model BIOMASS [19] into the asymptote of Schumacher's model, the authors reported a reduction of 7.7% in the mean quadratic error of the height estimates.

Considering the simulated conditions shown in Table 5, the values of dominant height varied from 18.7 to 35.1 m, which represents a range of 16.4 m. The highest values of dominant height found in the highest temperatures are in accordance with the optimum growing temperatures of 25°C for *Eucalyptus grandis* reported by Almeida et al. [20] for the parameterization of the 3PG model realized in the same study area. The last column of Table 5 presents a situation of an excess of precipitation that is equivalent to six standard deviations above the mean value, representing an annual precipitation of 2000 mm. Under these conditions the dominant height estimates were coherent, remaining within the range of the highest values of observed dominant height. It is important to note that biologically reasonable outputs of the equation are only achieved when the input variables are also reasonable, for example, inside or close to the range presented in Table 1.

4.1. Limitations and Use of the Proposed Methodology. It is recognized that the use of the proposed methodology to forecast growth is limited by the lack of future climate data. Even though the methods of meteorological forecasting are under constant evolution, it is prudent to limit the forecasting range to short periods of time, for example, one year.

A possible application of the proposed methodology is the estimation of site capacity in regions lacking any planting history. As shown in Figure 3, dominant height productivity curves in different sites can be obtained in function of historic climate data, aiding in the analysis of potential productivity. Conventional biometric formulations that do not consider climatic variables are not capable of this type of analysis. Since many other factors influence the productivity of forests (such as nutritional and genetic factors), it is prudent to limit the use of the equation generated in this study to regions close to the study area and with a similar climatic regime.

Another application of the method consists in model-based forest inventory database actualization to the present time. This type of application allows for updated timber stock estimation with greater certainty than traditional models, since the climatic conditions that the forest underwent through are known. This is also cheaper and faster than conducting a traditional timber cruising analysis.

Finally, productivity simulations considering different climatic scenarios are possible, enabling the realization of risk analysis based on the behavior of future climate conditions.

5. Conclusions

The alteration of the asymptotical parameter of the Chapman and Richards model by a coefficient modifier (Modi_A) obtained from the variables mean monthly precipitation and temperature allows for flexible and precise dominant height estimates, generating site classification curves with ecological bases.

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