

Article

A New Method to Calibrate Cardinal Temperatures for Eucalyptus Plantation [†]

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Abstract: Developing a good understanding of the interactions between forest plantation growth and climate is essential for predicting the impact of climate change on terrestrial ecosystems and for assessing the adaptation and vulnerability of tree species. One such interaction, the response in growth rate of a forest stand to changes in temperature, may be described mathematically. Some models that run on monthly time steps assume a yearly optimum, minimum, and maximum temperature for simplicity, which may not represent well to actual forest growth. Here, we developed a finer-resolution methodology that encompasses monthly growth rates and temperature limits to calibrate the parameters for an envelope curve in Eucalyptus plantations in South America. Several polynomial curves were tested to determine temperature patterns, and their yearly tree growth patterns demonstrated that responses to temperature differed by as much as 10 °C among seasons. The best curve was a second-degree polynomial curve, whose extreme values indicated the optimum temperature and whose real roots limited the minimum and maximum temperatures for growth. This polynomial was fitted every month to describe yearly changes in optimum, maximum, and minimum temperatures. When fitted to annual data, it determined 7 °C, 19 °C, and 31 °C as the minimum, optimum, and maximum temperatures for tree growth, respectively. The monthly model predictions indicated that the minimum, optimum, and maximum temperatures lay between 8 °C and 16 °C, 18 °C and 22 °C, and 27 °C and 30 °C, respectively. These monthly temperature ranges can improve the estimation of productivity in process-based models. Our results contribute to the understanding of tree growth dynamics and its relationship to changes in temperature. Accurate ranges of temperature can be used to improve productivity predictions in new expanding planting regions with no previous information or to suggest a regionalization for potential species.

Keywords: temperature range; Eucalyptus growth; second-degree polynomial curve

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1. Introduction

Environmental temperature is responsible for regulating the growth of trees; in addition, it is a key modulator in the synthesis of proteins which are responsible for lignification [1]. Ribulose 1,5-bisphosphate carboxylase/oxygenase (RuBisCo) is a key enzyme in the Calvin–Benson–Bassham cycle in plants and plays an important role in photosynthesis [2]. It is, therefore, responsible for the production of all biomass and needs specific conditions for its catalytic activation [3]. Ref. [4] reported that the rates of RuBP carboxylation, oxygenation, and electron transport increase in response to environmental temperature dynamics.

Air temperature is a common variable used in process-based models for modeling forest productivity, and it has been implemented in the following models: CARBON [5], ECOPHYS [6], BIOMASS [7], TREE BGC [8], 3-PG [9], and CABALA [10]. These models

predict the rate of tree growth and describe productivity on monthly, annual, and seasonal scales. Thus, the range of favorable temperatures that are used to summarize the response of the plant to air temperature can be called the cardinal temperature [11,12].

Threshold temperature can be determined using linear and nonlinear mathematical models that predict the influence of temperature on the growth of plants [13]. In linear models, the growth rate is assumed to be proportional to the interaction with temperature [14], whereas in nonlinear models, the response of plant growth to temperature changes is explained through a curve in which there is a peak of growth [15]. The nonlinear models, coupled with function-derived growth rates, can show new hypotheses about plant population and community ecology [16].

Modern systems for analyzing nonparametric data stimulate them to fit models with more flexibility and less assumption through the integration of stochastic processes and statistical models [17]. Some trees have unknown ecophysiologicals, owing to the lack of cultivation data under different climatic conditions. Despite the availability of numerous models for estimating cardinal temperatures, it is still unclear whether a linear or a nonlinear model would be more effective for such studies [13].

The accurate estimation of the effects of temperature on plant development improves the ability of growth simulation models to predict the impact of weather on growth rates and to explore the adaptation abilities of plants [18]. This is challenging because different phenological stages, as well as different processes of plant growth and development, have different temperature boundaries. Mathematical models represent an alternative to process-based dynamic models for predicting crop yields as a function of climatic conditions [19]. However, it is difficult to identify the behavior of the most relevant input variables for inclusion in regression models [20]. Models used to characterize real-world processes are affected by uncertainty and selecting an appropriate model is a vital aspect of the decision-making process in any study [21].

Regression models explore the dependency between variables using the least squares method [22] or maximum-likelihood sense [23]. However, this study provides the optimum cardinal temperatures based on the best-fit parameters for a nonlinear model using optimization capabilities. This study aims to calculate cardinal temperatures for growth of *Eucalyptus* plantations in South America, and to indicate the most appropriate model to be used for this purpose. The results can be used to establish the yearly and monthly acclimation patterns present in forest species.

2. Material and Methods

2.1. Experimental Data and Climatic Classification of Sites

This study is composed of data on *Eucalyptus* growth rates and air temperature measured in Brazil (six sites) and Uruguay (two sites). The study sites are part of the TECHS Cooperative Research Program (Tolerance of *Eucalyptus* Clones to Hydric, Thermal and Biotic Stresses), which started in 2011 in Brazil and Uruguay [24] (Figure 1). We selected eight TECHS sites planted from January to April 2012 covering a wide range of climates where most of the commercial *Eucalyptus* plantations are located, from Cfa (humid subtropical zone with hot summer and without dry season—Site 16 and 25), Cfb (humid subtropical zone with temperate summer and without dry season—Site 23), Cwb (humid subtropical zone with temperate summer and dry winter—Site 24), Cwa (humid subtropical zone with hot summer and dry winter—Site 20), As (tropical with dry summer—Site 30), and Aw (tropical with dry winter—Site 29 and 31).

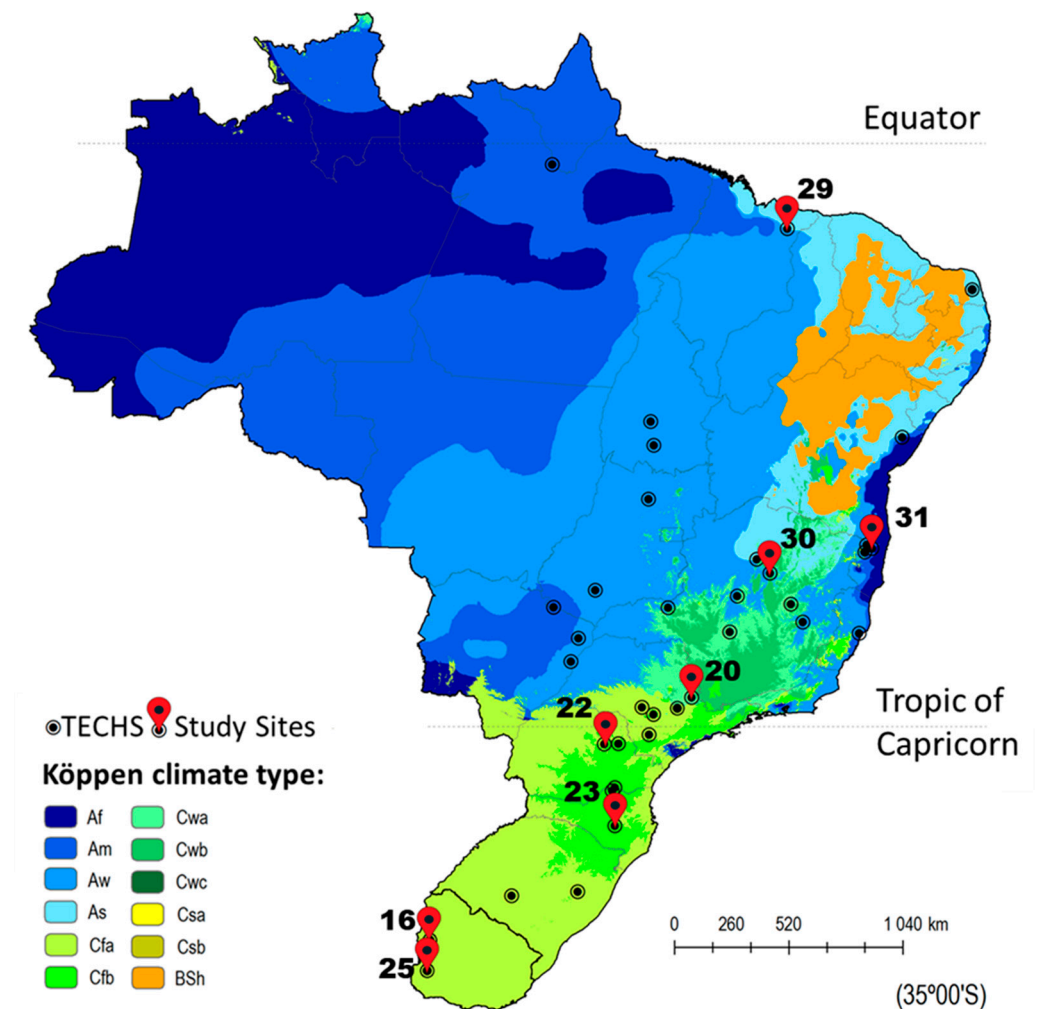


Figure 1. Geographic distribution of TECHS sites used for establishing the threshold temperature for *Eucalyptus urophylla* in South America. (Reprinted/adapted with permission from Ref. [25]. 2013, Alvares, C.A.; Stape, J.L.; Sentelhas, P.S.; Gonçalves, J.L.M.; Sparovek, G).

Figure 2 displays average monthly temperature from 8 contrasting sites. The sites covered a large temperature range (monthly average ranging from 12 °C to 27 °C) and were selected to represent climatic variability of in the climatic gradient that encompasses a wide range of temperature in South America. The curves extend from as far as the minimum to the maximum mean temperatures. During the period from 2012 to 2018 (6 years), the variation between the monthly averages of the maximum and minimum temperatures of the study sites was around to 10 °C to 30 °C.

Meteorological data were recorded at the meteorological stations in situ (S) at each experiment site. The minimum and maximum temperatures were recorded at 1 h intervals at all sites from 2012 to 2018. For our analysis, climatic data were aggregated on a daily basis. Days with more than four missing records (4 h in a row) were not considered when following our rigorous data processing setup [26]. These data were then compensated by from the meteorological data taken from other meteorological stations (I), i.e., the National Institute of Meteorology (INMET) and by the Instituto Nacional de Investigacion Agropecuaria (INIA), which are managed by the Brazilian and Uruguayan governments, respectively. Information about the location (latitude, longitude, and altitude) and distance between these meteorological stations are shown in Table 1. These meteorological stations (I) were chosen due to their proximity to the sites and the similarity in altitudes.

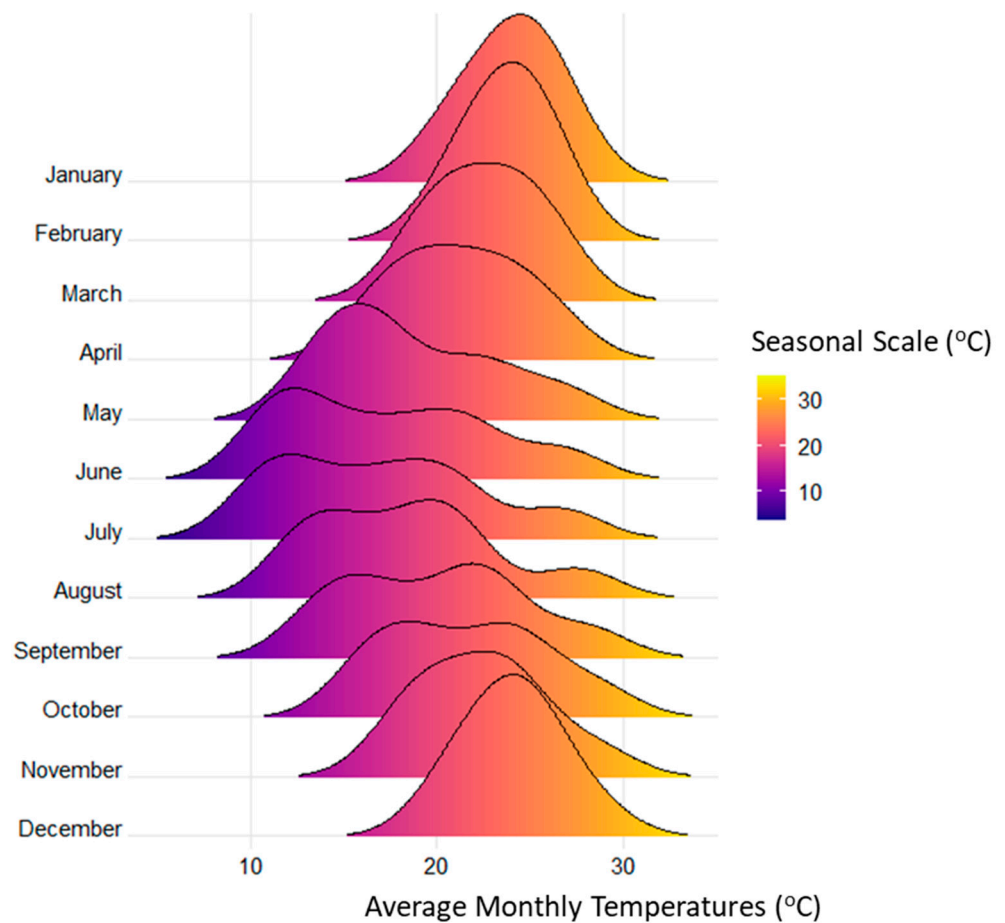


Figure 2. Analysis of average monthly temperatures (from January to December) from 2012 to 2018 based on the seasonality of the period.

Table 1. Comparison of the location of the TECHS sites with the location of the meteorological stations of either the National Institute of Meteorology (INMET) or the Instituto Nacional de Investigacion Agropecuaria (INIA).

Site	State/Country	Meteorological Station in Situ (S)			Meteorological Station from INMET or INIA * (I)			S ↔ I
		Lat	Long	Alt	Lat	Long	Alt	Distance
		Graus		Meters	Graus		Meters	Kilometers
16 *	Uruguay	−32.2	−57.8	50	−34.3	−57.7	72	112.9
20	Sao Paulo—Brazil	−22.4	−47.0	633	−22.0	−47.0	633	17.7
22	Parana—Brazil	−24.2	−50.5	888	−24.0	−50.0	1106	31.4
23	Santa Catarina—Brazil	−27.5	−50.1	870	−27.0	−51.0	982	53.5
25 *	Uruguay	−33.3	−57.9	37	−34.3	−57.7	47	103.8
29	Maranhao—Brazil	−3.4	−43.1	81	−4.0	−43.0	91	46.7
30	Minas Gerais—Brazil	−17.3	−43.8	848	−17.0	−44.0	646	64.6
31	Bahia—Brazil	−16.3	−39.6	200	−16.0	−39.0	88	47.6

* INMET—National Institute of Meteorology or INIA—Instituto Nacional de Investigacion Agropecuaria, which are managed by the Brazilian and Uruguayan governments, respectively.

Across the study sites, a commercial clone from *Eucalyptus urophylla*, widely planted in Brazil, was monitored every 15 to 30 days. Its choice is due to the satisfactory performance in tropical and subtropical regions [27]. This species occurs naturally over a wide latitudinal range from about 8 to about 10° S, especially in the islands of the West Timor, the islands of Flores, and the islands of Indonesian West Timor. Aw is the most common climate classification for this particular species, but it has been found in a lower proportion in Af,

Am, Cwa, and Cwb climate classification, and its annual thermal requirement is from 16 °C to 27 °C [28].

Diameter at breast height (DBH) was measured every 15 to 30 days from six trees at each site from 2014 to 2018 (4 years). Total height was calculated based on the forest inventory carried out every 6 months. Aboveground dry mass was estimated by harvesting 6 trees at each site ($n = 8$ trees/clone, totaling 96 trees). Destructive sampling was performed at 3 and 6 years after planting (mid and end of rotation) [29]. Dry mass equations for stems were fitted using the linearized model of Schumacher and Hall. Ref. [30] was fit to DBH and total height (TH) (Equation (1)).

$$\ln(BS) = \beta_0 + \beta_1 \ln(DBH_i) + \beta_2 \ln(TH_i) + e_i \quad (1)$$

where the generalized logarithmic model shows dry stem biomass (BS), diameter at breast (DBH_i), total height (TH_i), residual error (e_i), and the model parameters ($\beta_0, \beta_1, \beta_2$).

It is noteworthy that in this study, we did not analyze the biomass of leaves and branches. Parameters used for this function were $\hat{\beta}_0 = -5.12133$, $\hat{\beta}_1 = 2.11419$, and $\hat{\beta}_2 = 1.19044$, and the square of the adjusted R-squared (0.96), standard error (14.26), p -value (<0.0001), and minimum and maximum DBH (10.2 cm and 23.0 cm) are as shown in the following.

2.2. The Models

The growth models presented in this study were fitted for estimating the relative current increment of biomass. Here, models returned values in the growth range from 0 to 1, where 1 denotes maximum growth or potential growth. The coordinates of the peak for all functions represents the potential productivity (y) and optimum temperature for growth rate (x); thus, the Y axis received the name of growth rate modifier (GRM) and was defined as the adjustment of the maximum growth via a bordering sign of the potential productivity.

Model selection is a hard task; therefore, we used the four rules or guidelines established by [31]. The first rule postulates the use of fewer parameters in the model. Models that use more parameters than necessary showed poor estimation behavior, and this process was called overparameterization. The second rule postulates making decisions about the goodness-of-fit of your model, i.e., checking whether the model is satisfactory for interpreting data analysis behavior. The third rule is to apply the fit-most-complicated model, if the goodness-of-fit is not satisfactory. Finally, the last rule is to choose the model wherein the goodness-of-fit is improved.

The pre-selected models allow the use of inflection points, with a maximum and/or minimum value. The beta function has been used for explaining the behavior of the growth rate of the plant as a function of temperature [32]. Based on this function, the temperature modifier equation (Equation (2)) was developed, which describes the response of tree growth to air temperature [33].

$$f(x) = \left[\left(\frac{x - \beta_0}{\beta_2 - \beta_0} \right) \left(\frac{\beta_1 - x}{\beta_1 - T_0} \right)^{\frac{\beta_1 - \beta_2}{\beta_2 - \beta_0}} \right] \quad (2)$$

This model present three parameters, where $\beta_0 \leq x \leq \beta_1$, x = average monthly temperature (in °C); β_0 = minimum or base temperature; and β_2 = optimum air temperature. We compared a nonlinear beta function with a second-grade polynomial. However, the sigmoid pattern can be represented piecewise, using a linear and a convex equation sequentially [34,35]. The quadratic polynomial consists of a simple curve, and it also has three parameters (β_0, β_1 , and β_2). This function has a single maximum or minimum value, but without an inflection point (Equation (3)), and the parameter must be greater than 0 ($\beta_2 > 0$).

$$f(x) = \beta_2 x^2 + \beta_1 x + \beta_0 \quad (3)$$

In addition to these models, the inverse second-grade polynomial is a versatile model with three parameters (Equation (4)). It was used for describing the relationship between crop yield and number of plants per unit area [36].

$$f(x) = 1 / (\beta_2 x^2 + \beta_1 x + \beta_0) \quad (4)$$

A polynomial exponential is an elegant way of using a curvilinear equation and provides a gradual transition from one phase to the next [37]. In order to consider these possibilities, two functions were used (Equations (5) and (6)).

$$f(x) = \exp(\beta_2 x^2 + \beta_1 x + \beta_0) \quad (5)$$

$$f(x) = x^{\beta_0} * \exp(\beta_1 - \beta_2 * x) \quad (6)$$

Finally, we used a model that considered the ratio of the second-degree polynomial (Equation (5)):

$$f(x) = x / (\beta_2 x^2 + \beta_1 x + \beta_0) \quad (7)$$

2.3. Analytical Approach

For analysis of our data, we used the Data Envelopment Analysis (DEA) technique, which was initially used for describing the efficiency and productivity of economic systems through new models and interpretations [38]. In this study, we applied the same principle. The set of data for decision making in the time (t) in high frequency (t = 15 or 30, . . . , n) has non-negative inputs $x_t = (x_{1t}, \dots, x_{mt})$ and non-negative outputs $y_j = (y_{1t}, \dots, y_{st})$, i.e., mean temperature and growth rate, respectively.

The optimizer algorithm used for maximization of the regression models was inserted in the 'optimx' package [39] available for the R statistical language and environment [40]. The fitting parameters were simulated for each model through real numbers, which keeps the regression curve upper, at the same time, closer to the observed data.

3. Results and Discussion

3.1. Stem Dry Mass Production and Air Temperature

Stem dry biomass production of the *Eucalyptus urophylla* showed synchronization with the mean air temperature. The dynamics of the agreement of biomass accumulated in the stem is reduced when the temperature is higher than 22 °C. In South America, this occurrence increases with increasing latitudes (−32.2° S to −3.4° S) In these regions, the trees were able to synthesize up to 2 kg of dry biomass for stem. However, under limited resource conditions, the trees had stopped growth and development. Sites located in the subtropical region (Sites 16, 22, 23, and 25) presented monthly temperatures with peaks that reached temperatures around 25 °C, whereas sites located in tropical (Sites 20, 29, 30, and 31) presents longer periods with a range of among 21 °C and 26 °C. The biomass accumulated by trees is influenced by the maximum and minimum monthly average temperatures; therefore, it controls the onset or stoppage of tree growth. The following figure shows an appropriate visualization of this pattern (Figure S1).

The difference between the growth synchrony or growth rate for contrasting locations, in terms of dry stem biomass, DBH, or volume (Figure S2), depends on the inter- and intra-seasonal effects of temperature. Biomass accumulates breakpoints that depend on the species and the species adaptation to environmental conditions; therefore, the genetic variation in photosynthetic response can stimulate adaption. In this case, the stomatal responses to temperature affect the rate of carbon dioxide (CO₂) diffusion into the leaf which controls the internal CO₂ concentration and is responsible for the efficiency of carbon fixation [41].

The annual temperature range needed for plant growth provides an idea of the thermal requirements of plants. However, the temperature response occurs within a short time

of period; therefore, the seasonality among the months of the year cannot always be considered adequate indicators of annual mean temperature. Phenological events are regulated by temperature; therefore, it can stimulate the emergence of new shoots and the flowering of plants [42]. The flowering and growth of *Eucalyptus* depends on specific ranges of temperature, and the trees may be taller or shorter depending on the species and site characteristics [43,44]. Moreover, the effect of different temperatures on the metabolism of trees is responsible for either stimulating or causing the cessation of growth between phenological stages [45].

3.2. Growth Rate Modifier and Models

Nonparametric functions do not assume a particular form/shape for the experiment; however, it does provide a general overview of the relation between output (growth rate) and input (temperature). For the context of this study, the limit of the vertex simulation was established based on the premise that real tree productivity corresponds to only half of its potential productivity. According to [46], the loss is greater than 50% of the final yield when there are drought periods. Potential yield of plants depends on the amount of solar radiation received, efficient use of light, translocation of photosynthates in plants, and efficient synthesis of organic carbon from inorganic carbon [47,48]. Therefore, our simulations considered the limit for reaching the potential productivity which denotes the maximum growth rate (Equation (2)).

We carefully analyzed all the reasons that led to the rejection of some functions. In the first case, a curve was generated using the beta function (Equation (2)). This function establishes the limits of the range at which the data were observed. The same curve can be described for the polynomial function (Equation (3)) however, its limits are greater than those in the previous curve. For other models, the minimum and maximum temperature ranges are farther than the real points at which tree growth starts and ends (Equations (4)–(7)). Another noteworthy feature is the vertex of the Exponential Model (Equation (6)) that moves beyond potential productivity limits. Finally, the criteria to select the best model consisted of adding up the values of the integrand for each fitted function and then selecting the function with the lowest area per unit (Figure 3).

The function areas that were analyzed followed the order of the Quadratic Polynomial (Equation (3)) < beta function (Equation (2)) < Exp Quadratic Polynomial (Equation (5)) < Rate Polynomial (Equation (7)) < Inverse Quadratic Polynomial (Equation (4)) < Exp Model (Equation (6)). In this study, our results suggest that the Quadratic Polynomial was more adequate for fitting rate growth to air mean temperature because it can be defined as the lowest area per unit. Table 2 provides the parameters, area, and absolute error for each model that was studied.

The second-degree polynomial equation can be easily implemented to describe the yearly acclimation patterns present in forest species, as well as to improve process-based models. Nonmonotonic functions have the upside that each fort of a polynomial of degree ≥ 1 is a peak. In addition, forts of this function include peaks and points at the base of a platform, i.e., the range within which all values are at the same constant [34]. In this case, the discriminant can be used for discovering the ideal temperature for maximum growth (Equation (8)). In addition, the minimum and maximum temperature will be determined by two real roots (Equations (9) and (10)) that should have a discriminant greater than zero.

$$\text{Optimum Temperature (optT)} = \Delta = \beta_1^2 - 4 * \beta_2 * \beta_0 \quad (8)$$

$$\text{Minimum Temperature (minT)} = x_1 = \frac{(-\beta_1 + \sqrt{\text{optT}})}{2 * \beta_2} \quad (9)$$

$$\text{Maximum Temperature (maxT)} = x_2 = \frac{(-\beta_1 - \sqrt{\text{optT}})}{2 * \beta_2} \quad (10)$$

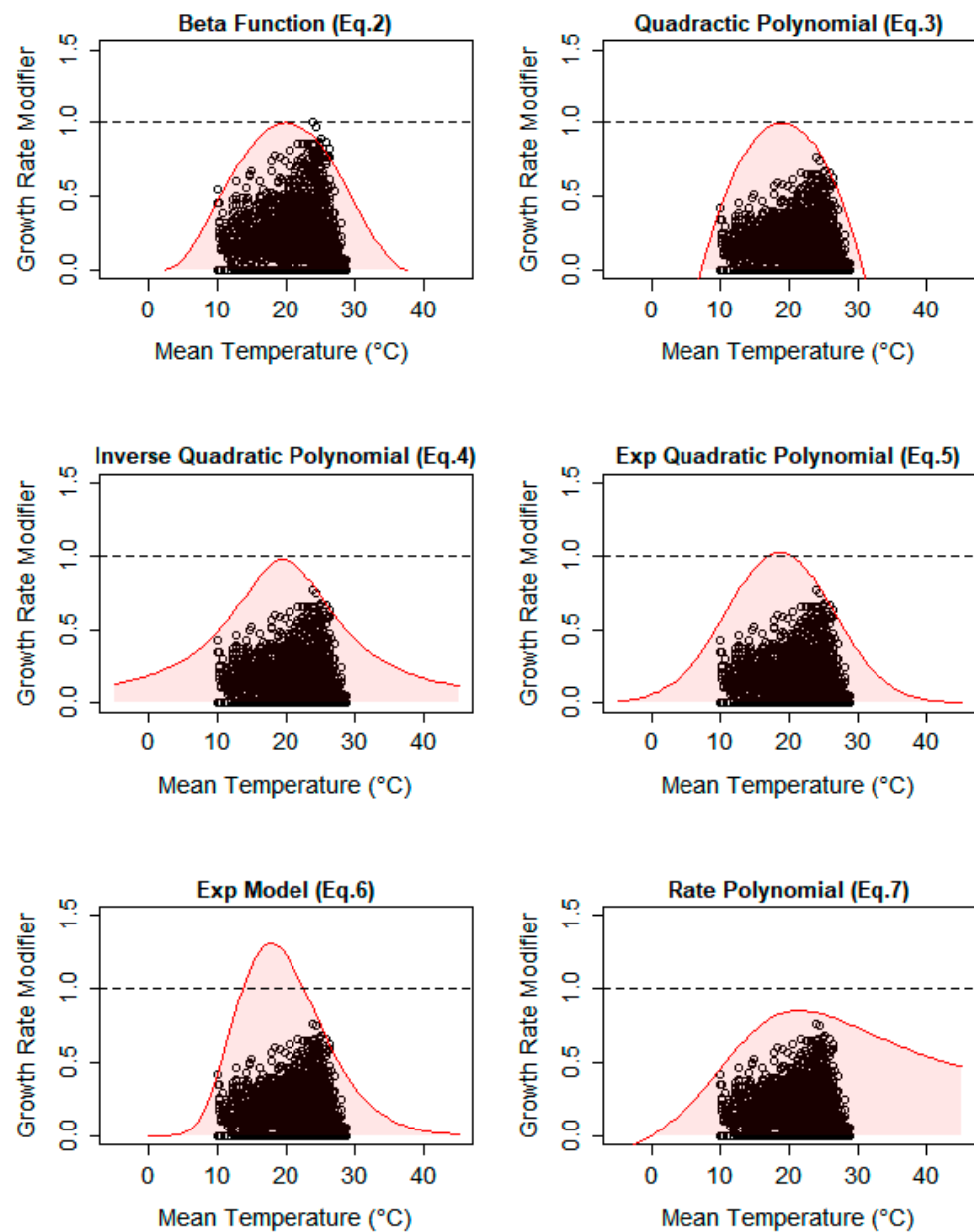


Figure 3. Models with optimized support regression curve with maxima and minima. The red background and boundary line define the limits of the data area.

Table 2. Model parameters with optimized support regression curve with maxima and minima for *Eucalyptus urophylla*.

Model	Name	$f(x)$	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	Area	Absolute Error
Equation (2)	Beta Function	$f(x) = \left[\frac{x-\beta_0}{\beta_2-\beta_0} \right] \left(\frac{\beta_1-x}{\beta_1-T_0} \right)^{\frac{\beta_1-\beta_2}{\beta_2-\beta_0}}$	2.2744	37.6508	19.9640	18.86794	$<6.5 \times 10^{-9}$
Equation (3)	Quadratic Polynomial	$f(x) = \beta_2x^2 + \beta_1x + \beta_0$	-1.5923	0.2732	-0.0072	15.69885	$<1.7 \times 10^{-13}$
Equation (4)	Inverse Quadratic Polynomial	$f(x) = 1/\beta_2x^2 + \beta_1x + \beta_0$	5.3897	-0.4481	0.0115	22.20823	$<2.9 \times 10^{-7}$
Equation (5)	Exp Quadratic Polynomial	$f(x) = \exp(\beta_2x^2 + \beta_1x + \beta_0)$	-2.8590	0.3094	-0.0083	19.92385	$<5.9 \times 10^{-5}$
Equation (6)	Exp Model	$f(x) = x^{\beta_0} * \exp(\beta_1 - \beta_2 * x)$	8.2905	-15.2678	0.4681	26.00404	$<1.7 \times 10^{-3}$
Equation (7)	Rate Polynomial	$f(x) = x/\beta_2x^2 + \beta_1x + \beta_0$	35.5476	-2.1410	0.0773	20.36569	$<2.1 \times 10^{-7}$

Fitting the quadratic function to the data facilitated the extraction of cardinal values in degree Celsius ($^{\circ}\text{C}$) for *Eucalyptus urophylla* in tropical and subtropical climatic conditions (Figure 4). The annual optimal air temperature for tree growth was 19°C , whereas the annual minimum and annual maximum temperatures needed to start and stop tree growth were 7°C and 31°C , respectively. The observations by [33] strengthen the idea that the climatic requirements of different *Eucalyptus* species range between temperatures of 15°C and 27°C for the optimum temperature, between 3°C and 6°C for the minimum temperature, and between 22°C and 30°C for the maximum temperature. However, these authors used a fitted beta function in their models, which resulted in the underperformance of the former in the determination of threshold temperature for growing *Eucalyptus urophylla*.

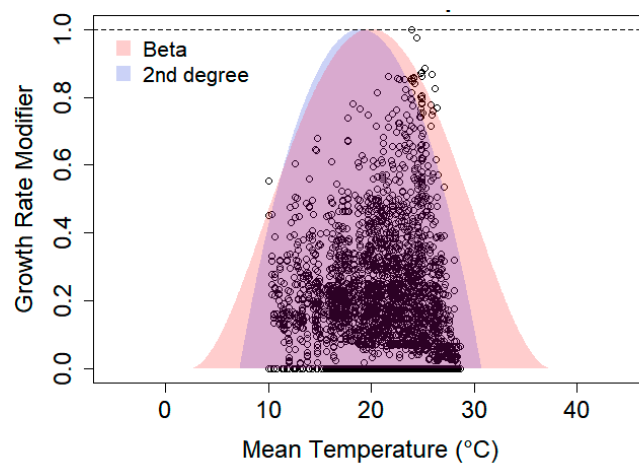


Figure 4. Beta function and quadratic models with optimized support regression curve for *Eucalyptus urophylla* on an annual scale.

3.3. Cardinal Temperature and Process-Based Models

The beta function was used [49] for describing the effect of temperature on the rate of crop rice growth. Later, process-based models, such as the 3-PG (Physiological Principles Predicting Growth) model developed by Landsberg and Waring 1997 [50], incorporated the same function to improve the models for studying forest growth. Recently, the annual thermal requirement of *Eucalyptus urophylla* discovered through this study showed a high performance in the 3-PG model [51], so the optimized support regression curve is a way to determine the acclimation patterns of trees and suggest improvements in process-based models.

We compared the beta distribution reported in the literature with a second-degree polynomial equation. This was the first step for understanding the dynamics of *Eucalyptus* growth; after that, we analyzed the beta function with the second-degree polynomial equation on a monthly scale. This relationship between tree growth and second-degree polynomial equation became stronger and more evident when we analyzed high-resolution time scales (Figure 5).

The second-degree function was also able to describe the temperature range required for tree growth on the monthly scale. The fitted function followed the same process from simulation for identifying model parameters, area, and absolute error for each model studied (Table 3). We believe that this determination can drive management decisions based on expected scenarios of climate change and the thermal requirements for *Eucalyptus urophylla*. Most of the months fitted the growth rate to air mean temperature with the lowest area per unit; therefore, our results also recommend that the quadratic polynomial is more adequate for explaining variations throughout the year.

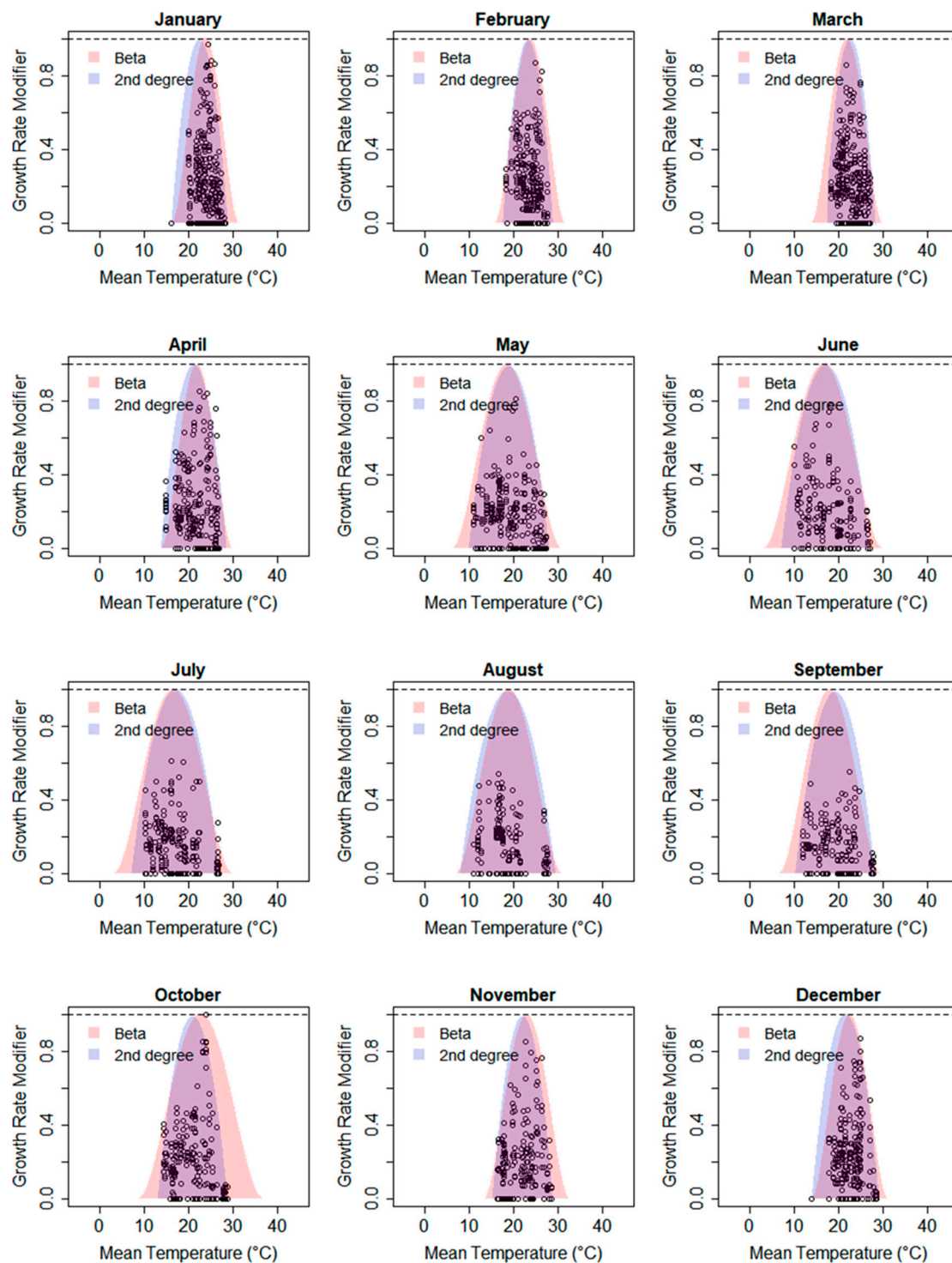


Figure 5. Beta function and quadratic models with optimized support regression curve for *Eucalyptus urophylla* on a monthly scale.

Based on monthly average temperatures and the high frequency monitoring of tree growth, monthly temperature ranges were identified for each month. The monthly acclimation patterns of *Eucalyptus urophylla* in the contrasting weather of South America are indicated in Table 4.

Table 3. Quadratic model and beta function parameters with optimized support regression curve and cardinal temperature for *Eucalyptus urophylla*.

Month	2nd Degree Polynomial					Beta Function				
	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	Area	Absolute Error	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	Area	Absolute Error
January	-11.5092	1.1100	-0.0246	8.4520	$<9.4 \times 10^{-14}$	16.1375	23.3863	31.4918	8.0729	$<4.9 \times 10^{-5}$
February	-15.7086	1.4359	-0.0309	7.5211	$<8.4 \times 10^{-14}$	15.6712	23.4399	31.7432	8.4867	$<2.8 \times 10^{-5}$
March	-14.8584	1.4004	-0.0309	7.5279	$<8.4 \times 10^{-14}$	13.7724	21.6694	30.0155	8.5889	$<2.2 \times 10^{-5}$
April	-7.1868	0.7713	-0.0182	9.8281	$<1.1 \times 10^{-13}$	13.7724	21.6694	30.0155	8.5889	$<2.2 \times 10^{-5}$
May	-3.3387	0.4562	-0.0120	11.9704	$<1.3 \times 10^{-13}$	6.0409	18.2299	30.9412	13.1905	$<2.4 \times 10^{-5}$
June	-1.9104	0.3395	-0.0099	13.3144	$<1.5 \times 10^{-13}$	3.0467	16.2665	30.0540	14.3065	$<2.6 \times 10^{-5}$
July	-1.9210	0.3409	-0.0100	13.3400	$<1.5 \times 10^{-13}$	3.0467	16.2665	30.0540	14.3065	$<2.6 \times 10^{-5}$
August	-2.0265	0.3219	-0.0086	14.2415	$<1.6 \times 10^{-13}$	6.8377	18.8862	31.0061	12.8763	$<1.4 \times 10^{-6}$
September	-3.5280	0.4690	-0.0122	11.8531	$<1.3 \times 10^{-13}$	6.5255	17.8706	29.5968	12.2376	$<1.6 \times 10^{-5}$
October	-6.0212	0.6695	-0.0160	10.4198	$<1.2 \times 10^{-13}$	8.5334	22.1008	36.9952	14.9869	$<7.4 \times 10^{-5}$
November	-9.3220	0.9343	-0.0212	9.0602	$<1 \times 10^{-13}$	13.2544	22.8786	32.7458	10.3517	$<9 \times 10^{-6}$
December	-7.1279	0.7536	-0.0175	10.1607	$<1.1 \times 10^{-13}$	13.8997	22.4568	31.1807	9.1860	$<5.5 \times 10^{-6}$

Table 4. Quadratic model parameters with optimized support regression curve and cardinal temperatures for *Eucalyptus urophylla*.

Month	Minimum Temperature ($minT$ —°C)	Optimum Temperature ($optT$ —°C)	Maximum Temperature ($maxT$ —°C)
	$minT = \frac{(+\beta_1 + \sqrt{optT})}{2 * \beta_2}$	$optT = \beta_1^2 - 4 * \beta_2 * \beta_0$	$maxT = \frac{(+\beta_1 - \sqrt{optT})}{2 * \beta_2}$
January	16.2	22.5	28.9
February	17.6	23.3	28.9
March	17.0	22.7	28.3
April	13.8	21.2	28.6
May	9.9	19.0	28.1
June	7.1	17.1	27.2
July	7.1	17.1	27.2
August	8.0	18.8	29.5
September	10.3	19.3	28.3
October	13.1	21.0	28.8
November	15.2	22.1	28.9
December	14.0	21.6	29.2

To make it easier to understand, we classified the temperature range that we discovered for growing *Eucalyptus urophylla* in tropical and subtropical climatic conditions (Figure 6). The following boxplot shows each mean temperature range (minimum, optimum, and maximum). The red diamond inside the box is the monthly average temperature. The whiskers, the two lines at either end, extend from the box as far as the minimum and maximum mean temperature for each temperature range. The lowest seasonal average minimum temperature for starting the growth of the trees was observed in May, June, July, and August. The minimum temperatures in this period reached values ranging from 7 °C to 10 °C. In the same period, the average monthly optimum temperature for maximum growth was 18 °C (± 0.87 °C). However, the minimum temperatures in the months of January, February, March, and April had values that ranged from 14 °C to 18 °C, whereas in the months of September, October, November, and December, the average monthly temperature for starting Eucalyptus growth lay between 10 °C and 15 °C. The optimum temperature for the four initial and the four final months of the year was around to 22 °C. Overall, the average maximum temperature for stopping growth is 29 °C, and it had a lower standard deviation (± 0.71 °C).

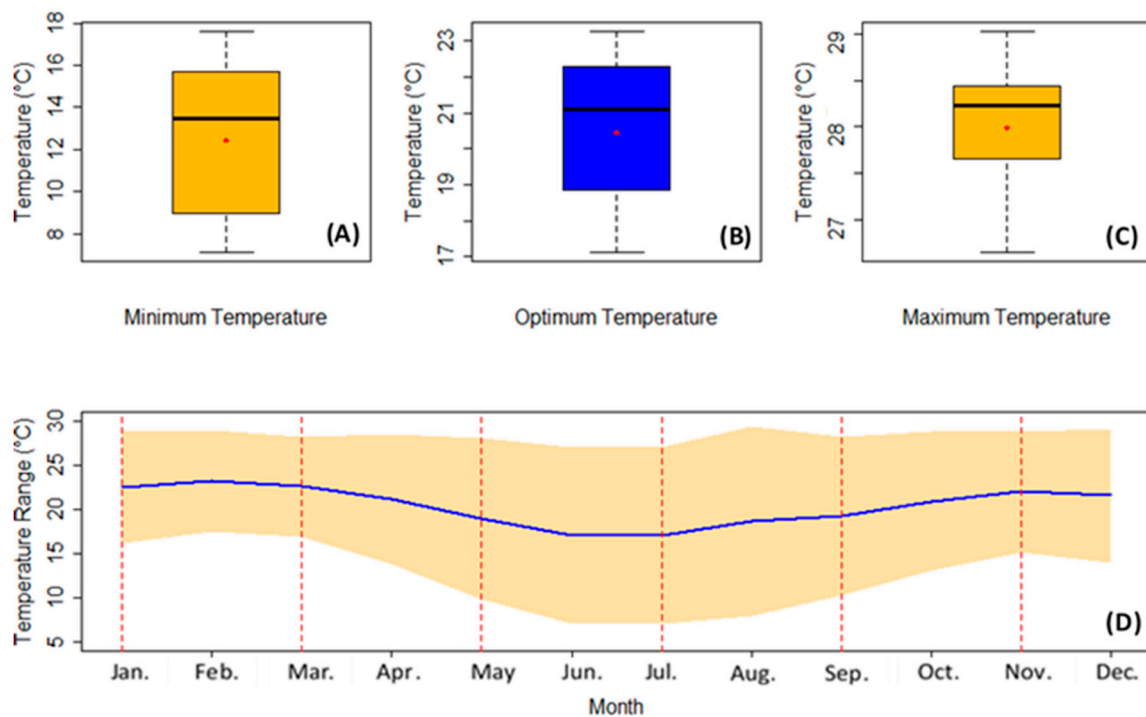


Figure 6. Minimum (A), optimum (B), and maximum (C) mean temperature ranges are represented by boxplots, along with the cardinal temperature for growing *Eucalyptus urophylla* under tropical and subtropical climatic conditions, depicted by blue lines. The amplitude of these ranges is represented by an orange-colored area (D).

Finally, we are faced with the following question: if we use a monthly temperature range, can we improve process-based models? The deductive manner developed here shows that our results are logically developed and that we used monthly mean temperatures in association with growth rates. Therefore, this scale becomes more appropriate for studying the phenological behavior of plants. The variation in temperature determines the biological activities of the cells, and therefore, it regulates the growth of the trees through temperature synchronization with carbon assimilation, as can be seen in Figure 3. Furthermore, it is not possible to assess proper physiological information on a yearly or rotational time scale. Presumably, the most frequent mistake of a process-based model is to assume that seasonal variability does not exist. In most cases, insufficiently sampled data are processed at an inappropriate scale, which then shows a reduced accuracy of results.

The growth rate modifier map created using second-degree polynomial equation can be used to selected for predictors of optimum temperature. Except for the first trimester, the model showed that the Central region maintained a value close to 1 (Figure 7). So, this region had the highest predicted tree productivity based on mean temperature. The south side of South America had gradually reduced productivity for plant growth. Growth rate increases were lower during the winter season (June–July), when temperatures were relatively low; this effect was more pronounced in the South region. Overall, we concluded that the dark areas with a mean temperature below 7 °C experienced a drastically reduced growth rate (value close to 0) for trees, while the average maximum temperature for stopping growth is around to 30 °C. The Legal Amazon area represents the geographic borders of the political region under the jurisdiction of SUDAM—established by Article 2 of Complementary Law no. 124, of 3 January 2007—which promotes its inclusive and sustainable development in order to integrate the local production into the national and international economy, according to [51].

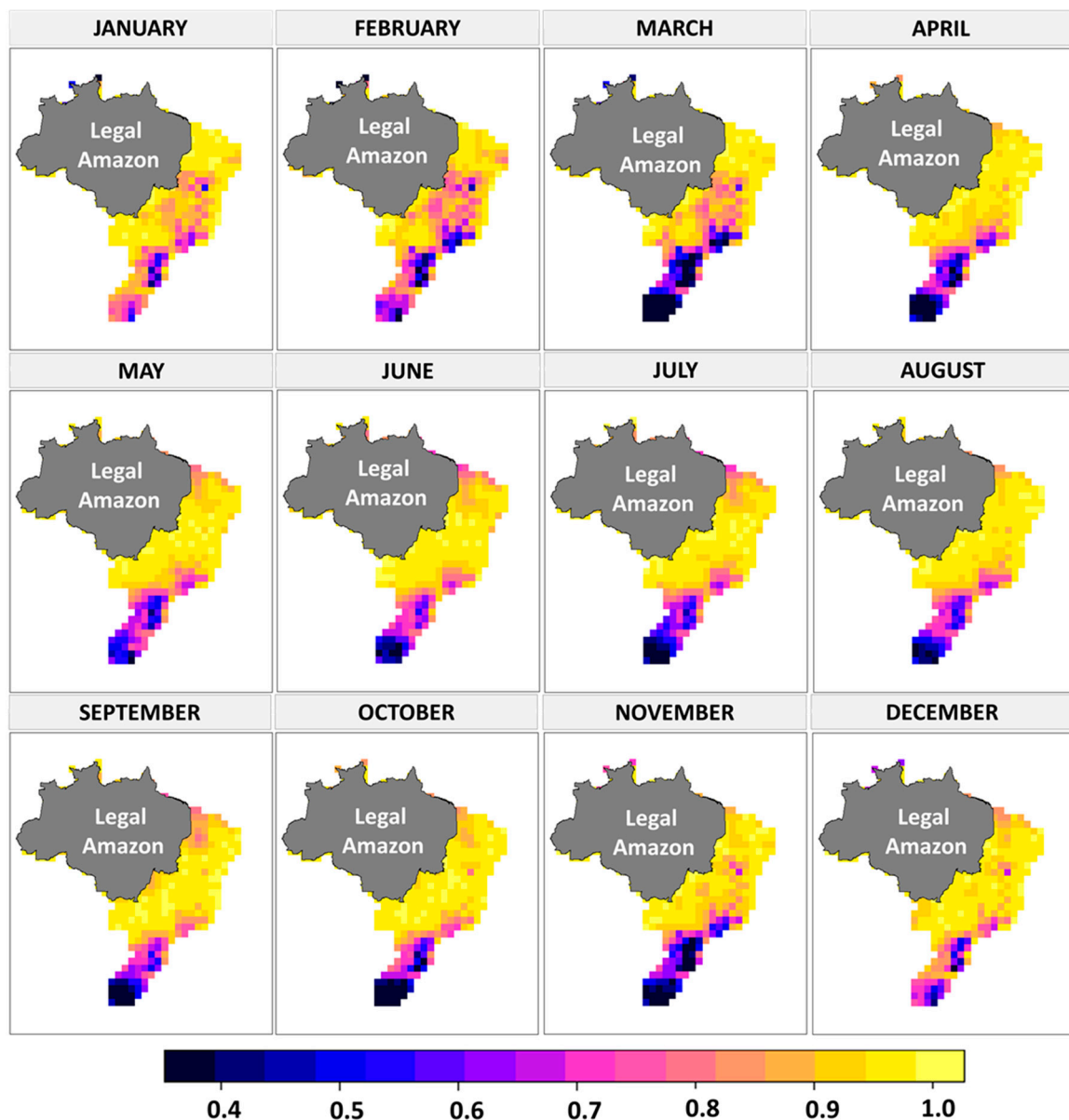


Figure 7. Quadratic model with optimized support regression based on mean temperature range optimum for growing *Eucalyptus urophylla* in tropical and subtropical climatic conditions.

The reduction in the enzymatic activity and reduction in the membrane flexibility are two main direct effects of low temperature [52]. When plants are incapacitated due to this effect, it causes cellular damage or death, and the widespread variation in biochemical responses depends on the genetic and physiological differences between different species [53]. High-temperature conditions that exceed the threshold level are responsible for causing irreversible injury/harm to overall plant growth, metabolism, and productivity [54]. Very high temperatures (above 40 °C) weaken root growth and can kill them [55]. Our study determined that tree growth in South America happens at an average temperature of up to 29 °C; however, it is worth remembering that during the hottest periods of the year, monthly temperature can fall to 10 °C, so the stress time was directly related to the proportion of the damage and monthly average temperature. Temperatures above 40 °C caused serious damage to photosystem II, which did not recover when heat stress lasting more than 15 min occurred [35]. Finally, appropriate genotypes should be recommended for an area according to their thermal requirements. Thus, the evidence of our findings shows us

why we must take into account monthly temperatures, and why it is important to study the annual pattern to estimate biological processes.

4. Conclusions

A second-degree model has been fitted to describe tree cardinal temperatures. The main features of this model can be summarized as the detection of minimum, optimum, and maximum temperatures required for tree growth on the annual and monthly scale.

The knowledge of temperature range required for tree growth is important to optimize process-based prognosis models, in addition to selecting suitable species depending on the climatic conditions of the region, and consequently to improve the yield and support genetic breeding programs.

The temperature ranges needed to maintain tree growth show variations throughout the year. Mean annual values undoubtedly improve the quality of the model; however, the variability between months should be considered for accurate estimates. As a result of this study, growth modelers will be able to use adequate temperature data to predict the productivity in *Eucalyptus* plantations.

Finally, in times of climate change, forest species with good adaptation potential can be more often recommended based on thermal requirements. The thermal amplitude studied in tropical and subtropical regions of South America can be a reference for decision making in other regions of the world with potential for the development of the forest sector.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/f14081631/s1>, Figure S1: Bi-weekly monitoring of mean air temperature and stem biomass of *Eucalyptus urophylla* cultivated from 2012 to 2018 across South America, Figure S2: Diameter (A) and stem volume (B) were measured throughout the planting months for each site studied in South America.

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References

1. Costa, M.G.S.; Mazzafera, P.; Balbuena, T.S. Insights into Temperature Modulation of the *Eucalyptus Globulus* and *Eucalyptus Grandis* Antioxidant and Lignification Subproteomes. *Phytochemistry* **2017**, *137*, 15–23. [CrossRef]
2. Matsumoto, K.; Juri, S.; Toshinori, Y.; Hori, C.; Nagata, A.; Kudoh, Y.; Ooi, T.; Taguchi, S. Ribulose-1,5-Bisphosphate Carboxylase/Oxygenase (RuBisCO)-Mediated de Novo Synthesis of Glycolate-Based Polyhydroxyalkanoate in *Escherichia Coli*. *J. Biosci. Bioeng.* **2019**, *128*, 302–306. [CrossRef] [PubMed]
3. Bhat, J.Y.; Miličić, G.; Thieulin-Pardo, G.; Bracher, A.; Maxwell, A.; Ciniawsky, S.; Mueller-Cajar, S.; Engen, J.R.; Hartl, F.U.; Wendler, P.; et al. Mechanism of Enzyme Repair by the AAA+ Chaperone Rubisco Activase. *Mol. Cell* **2017**, *67*, 744–756.e6. [CrossRef] [PubMed]
4. Greer, D.H. The short-term temperature-dependency of CO₂ photosynthetic responses of two *Vitis vinifera* cultivars grown in a hot climate. *Environ. Exp. Bot.* **2018**, *147*, 125–137.

5. Bassow, S.L.; Ford, E.D.; Kiester, A.R. A Critique of Carbon-Based Tree Growth Models. In *Process Modeling of Forest Growth Responses to Environmental Stress*; Timber Press: Portland, OR, USA, 1990; pp. 50–57.
6. Rauscher, H.M.; Isebrands, J.G.; Host, G.E.; Dickson, R.E.; Dickmann, D.I.; Crow, T.R.; Michael, D.A. ECOPHYS: An Ecophysiological Growth Process Model for Juvenile Poplar. *Tree Physiol.* **1990**, *7*, 255–281. [[CrossRef](#)]
7. McMurtrie, R.E.; Rook, D.A.; Kelliher, F.M. Modelling the Yield of *Pinus Radiata* on a Site Limited by Water and Nitrogen. *For. Ecol. Manag.* **1990**, *30*, 381–413. [[CrossRef](#)]
8. Korol, R.L.; Running, S.W.; Milner, K.S. Incorporating Intertree Competition into an Ecosystem Model. *Can. J. For. Res.* **1995**, *25*, 413–424. [[CrossRef](#)]
9. Landsberg, J.J.; Waring, R.H. A Generalised Model of Forest Productivity Using Simplified Concepts of Radiation-Use Efficiency, Carbon Balance and Partitioning. *For. Ecol. Manag.* **1997**, *95*, 209–228. [[CrossRef](#)]
10. Battaglia, M.; Sands, P.; White, D.; Mummery, D. CABALA: A Linked Carbon, Water and Nitrogen Model of Forest Growth for Silvicultural Decision Support. *For. Ecol. Manag.* **2004**, *193*, 251–282.
11. Rouan, L.; Audebert, A.; Luquet, D.; Roques, S.; Dardou, A.; Gozé, E. Cardinal Temperatures Variability within a Tropical *Japonica* Rice Diversity Panel. *Plant Prod. Sci.* **2018**, *21*, 256–265. [[CrossRef](#)]
12. Baath, G.S.; Kakani, V.G.; Gowda, P.H.; Rocateli, A.C.; Northup, B.K.; Singh, H.; Katta, J.R. Guar Responses to Temperature: Estimation of Cardinal Temperatures and Photosynthetic Parameters. *Ind. Crops Prod.* **2019**, *145*, 111940. [[CrossRef](#)]
13. Andreucci, M.P.; Moot, D.J.; Black, A.D.; Sedcole, R. A Comparison of Cardinal Temperatures Estimated by Linear and Nonlinear Models for Germination and Bulb Growth of Forage Brassicas. *Eur. J. Agron.* **2016**, *81*, 52–63. [[CrossRef](#)]
14. Daibes, L.F.; Cardoso, V.J.M. Seed Germination of a South American Forest Tree Described by Linear Thermal Time Models. *J. Therm. Biol.* **2018**, *76*, 156–164. [[CrossRef](#)]
15. Ryan, M.G. Temperature and Tree Growth. *Tree Physiol.* **2010**, *30*, 667–668. [[CrossRef](#)] [[PubMed](#)]
16. Paine, C.E.; Timothy Toby, R.M.; Vogt, D.R.; Purves, D.; Rees, M.; Hector, A.; Turnbull, L.A. How to Fit Nonlinear Plant Growth Models and Calculate Growth Rates: An Update for Ecologists: Nonlinear Plant Growth Models. *Methods Ecol. Evol.* **2012**, *3*, 245–256. [[CrossRef](#)]
17. Warr, R.L.; Collins, D.H. Bayesian Nonparametric Models for Combining Heterogeneous Reliability Data. *Proc. Inst. Mech. Eng. Part O J. Risk Reliab.* **2014**, *228*, 166–175. [[CrossRef](#)]
18. Luo, Q. Temperature Thresholds and Crop Production: A Review. *Clim. Chang.* **2011**, *109*, 583–598. [[CrossRef](#)]
19. Sharif, B.; Makowski, D.; Plauborg, F.; Olesen, J.E. Comparison of Regression Techniques to Predict Response of Oilseed Rape Yield to Variation in Climatic Conditions in Denmark. *Eur. J. Agron.* **2017**, *82*, 11–20. [[CrossRef](#)]
20. Kim, S.; Kano, M.; Nakagawa, H.; Hasebe, S. Input Variable Scaling for Statistical Modeling. *Comput. Chem. Eng.* **2015**, *74*, 59–65. [[CrossRef](#)]
21. Shoaib, S.A.; Marshall, L.; Sharma, A. Attributing Uncertainty in Streamflow Simulations Due to Variable Inputs via the Quantile Flow Deviation Metric. *Adv. Water Resour.* **2018**, *116*, 40–55. [[CrossRef](#)]
22. Souza, L.C.; Souza, R.M.C.R.; Amaral, G.J.A.; Silva Filho, T.M. A Parametrized Approach for Linear Regression of Interval Data. *Knowl. Based Syst.* **2017**, *131*, 149–159. [[CrossRef](#)]
23. González, M.; Minuesa, C. del Puerto, I. Maximum Likelihood Estimation and Expectation–Maximization Algorithm for Controlled Branching Processes. *Comput. Stat. Data Anal.* **2016**, *93*, 209–227. [[CrossRef](#)]
24. Binkley, D.; Campor, O.C.; Alvares, C.; Carneiro, R.L.; Cegatta, I.; Stape, J.L. The Interactions of Climate, Spacing and Genetics on Clonal Eucalyptus Plantations across Brazil and Uruguay. *For. Ecol. Manag.* **2017**, *405*, 271–283. [[CrossRef](#)]
25. Alvares, C.A.; Stape, J.L.; Sentelhas, P.S.; Gonçalves, J.L.M.; Sparovek, G. Koppen’s Climate Classification Map for Brazil. *Meteorol. Zeitschrift* **2013**, *22*, 711–728. Available online: http://www.lerf.eco.br/img/publicacoes/Alvares_et_al_2014.pdf (accessed on 1 July 2023).
26. Elli, E.F.; Sentelhas, P.C.; Freitas, C.H.; Carneiro, R.L.; Alvares, C.A. Intercomparison of Structural Features and Performance of Eucalyptus Simulation Models and Their Ensemble for Yield Estimations. *For. Ecol. Manag.* **2019**, *450*, 117493. [[CrossRef](#)]
27. Gonçalves, J.L.M.; Alvares, C.A.; Higac, A.R.; Silva, L.D.; Alfenas, A.C.; Stahl, J.; Ferras, S.F.; Lima, W.P.; Brancalion, P.H.S.; Hubner, A.; et al. Integrating genetic and silvicultural strategies to minimize abiotic and biotic constraints in Brazilian eucalypt plantations. *For. Ecol. Manag.* **2013**, *301*, 6–27. [[CrossRef](#)]
28. Flores, T.B.; Alvares, C.A.; Souza, V.C.; Stape, J.L. *Eucalyptus No Brasil: Zonemaneto Climático e Guia Para Identificação*; IPEF: Piracicaba, Brazil, 2016.
29. Campoe, O.C.; Alvares, C.A.; Carneiro, R.L.; Binkley, D.; Ryan, G.; Hubbard, R.M.; Stahl, J.; Moreira, G.; Moraes, F.; Stape, J.L. Climate and genotype influences on carbon fluxes and partitioning in Eucalyptus plantations. *For. Ecol. Manag.* **2020**, *475*, 118445. [[CrossRef](#)]
30. Schumacher, F.X.; Hall, F.S. Logarithmic Expression of Tree Volume. *J. Agric. Res.* **1933**, *47*, 719–734.
31. Ratkowsky, D.A. *Handbook of Nonlinear Regression Models*; M. Dekker: New York, NY, USA, 1990.
32. Yin, X.; Martin, J.K.; McLaren, G.; Visperas, R.M. A Nonlinear Model for Crop Development as a Function of Temperature. *Agric. For. Meteorol.* **1995**, *77*, 1–16. [[CrossRef](#)]
33. Watt, M.S.; Rubilar, R.; Kimberley, M.O.; Kriticos, D.J.; Emhart, V.; Mardones, O.; Acevedo, M.; Pincheira, M.; Stape, J.; Fox, T. Using Seasonal Measurements to Inform Ecophysiology: Extracting Cardinal Growth Temperatures for Process-Based Growth Models of Five Eucalyptus Species/Crosses from Simple Field Trials. *N. Z. J. For. Sci.* **2014**, *44*, 9. [[CrossRef](#)]

34. Yu, Z.; Weinian, Z. Forts of Quadratic Polynomials under Iteration. *J. Comput. Appl. Math.* **2018**, *331*, 1–10. [[CrossRef](#)]
35. Zhang, K.; Chen, B.-h.; Hao, Y.; Yang, R.; Wang, Y.-a. Effects of Short-Term Heat Stress on PSII and Subsequent Recovery for Senescent Leaves of *Vitis Vinifera*, L. Cv. Red Globe. *J. Integr. Agric.* **2018**, *17*, 2683–2693. [[CrossRef](#)]
36. Holliday, R. Plant Population and Crop Yield. *Nature* **1960**, *186*, 22–24. [[CrossRef](#)]
37. Goudriaan, J.; Monteith, J.L. A Mathematical Function for Crop Growth Based on Light Interception and Leaf Area Expansion. *Ann. Bot.* **1990**, *66*, 695–701. [[CrossRef](#)]
38. Charnes, A.; Cooper, W.W.; Rhodes, E. Measuring the Efficiency of Decision Making Units. *Eur. J. Oper. Res.* **1978**, *2*, 429–444. [[CrossRef](#)]
39. Nash, J.C.; Ravi, V.; Gabor, G. Expanded Replacement and Extension of the ‘optim’ Function. 2018. Available online: <https://cran.rstudio.com/web/packages/optimx/optimx.pdf> (accessed on 1 November 2022).
40. R Core Team. R: A Language and Environment for Statistical Computing. 2014. Available online: <http://www.Rproject.org/> (accessed on 6 June 2022).
41. Ocheltree, T.W.; Nippert, J.B.; Prasad, P.V.V. Stomatal Responses to Changes in Vapor Pressure Deficit Reflect Tissue-Specific Differences in Hydraulic Conductance: Stomatal Sensitivity of C3 and C4 Grasses. *Plant Cell Environ.* **2014**, *37*, 132–139. [[CrossRef](#)]
42. Hänninen, H.; Kramer, K.; Tanino, K.; Zhang, R.; Wu, J.; Fu, Y.H. Experiments Are Necessary in Process-Based Tree Phenology Modelling. *Trends Plant Sci.* **2019**, *24*, 199–209. [[CrossRef](#)] [[PubMed](#)]
43. King, G.; Fonti, P.; Nievergelt, D.; Büntgen, U.; Frank, D. Climatic Drivers of Hourly to Yearly Tree Radius Variations along a 6 °C Natural Warming Gradient. *Agric. For. Meteorol.* **2013**, *168*, 36–46. [[CrossRef](#)]
44. Rawal, D.S.; Sabine, K.; Keatley, M.R.; Nitschke, C.R. Climatic and Photoperiodic Effects on Flowering Phenology of Select Eucalypts from South-Eastern Australia. *Agric. For. Meteorol.* **2015**, *214–215*, 231–242. [[CrossRef](#)]
45. Svystun, T.; Bhalerao, R.P.; Jönsson, A.M. Modelling Populus Autumn Phenology: The Importance of Temperature and Photoperiod. *Agric. For. Meteorol.* **2019**, *271*, 346–354. [[CrossRef](#)]
46. Bartels, D.; Sunkar, R. Drought and Salt Tolerance in Plants. *Crit. Rev. Plant Sci.* **2005**, *24*, 23–58. [[CrossRef](#)]
47. Ranalli, P. *Improvement of Crop Plants for Industrial End Uses*; Springer: Dordrecht, The Netherlands, 2007; 533p.
48. Long, S.P.; Zhu, X.-G.; Naidu, S.L.; Ort, D.R. Can Improvement in Photosynthesis Increase Crop Yields? *Plant Cell Environ.* **2006**, *29*, 315–330. [[CrossRef](#)] [[PubMed](#)]
49. Sands, P.J.; Landsberg, J.J. Parameterisation of 3-PG for Plantation Grown Eucalyptus Globulus. *For. Ecol. Manag.* **2002**, *163*, 273–292. [[CrossRef](#)]
50. Caldeira, D.R.M.; Alvares, C.A.; Campoe, O.C.; Hakamada, R.E.; Guerrini, I.A.; Cegatta, I.R.; Stape, J.L. Multisite Evaluation of the 3-PG Model for the Highest Phenotypic Plasticity Eucalyptus Clone in Brazil. *For. Ecol. Manag.* **2020**, *462*, 117989. [[CrossRef](#)]
51. Information, E.; Portal, N. Legal Amazon | IBGE. 2022. Available online: <https://www.ibge.gov.br/en/geosciences/environmental-information/vegetation/17927-legal-amazon.html?=&t=o-que-e> (accessed on 13 April 2022).
52. Zoldan, D.; Band, R.S.; Guy, C.L.; Porat, R. Understanding Chilling Tolerance Traits Using Arabidopsis Chilling-Sensitive Mutants. In *Environmental Adaptations and Stress Tolerance of Plants in the Era of Climate Change*; Ahmad, P., Prasad, M.N.V., Eds.; Springer: New York, NY, USA, 2012; pp. 159–173. [[CrossRef](#)]
53. Raju, S.K.K.; Barnes, A.C.; Schnable, J.C.; Roston, R.L. Low-Temperature Tolerance in Land Plants: Are Transcript and Membrane Responses Conserved? *Plant Sci.* **2018**, *276*, 73–86. [[CrossRef](#)]
54. Wahid, A.; Gelani, S.; Ashraf, M.; Foolad, M. Heat Tolerance in Plants: An Overview. *Environ. Exp. Bot.* **2007**, *61*, 199–223. [[CrossRef](#)]
55. Celestian, S.B.; Martin, C.A. Rhizosphere Surface, and Air Temperature Patterns at Parking Lots in Phoenix, Arizona, U.S. *J. Arboric.* **2004**, *30*, 245–252.

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