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Estimating Sugarcane Yield in a Subtropical Climate Using Climatic Variables and Soil Water Storage

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Abstract: Brazil is the largest producer of sugarcane (*Saccharum* spp.) in the world, and this crop's response to climate and soil water storage is essential for optimal management and genetic/yield improvements. The objective of our study was to build a multivariate model to estimate sugarcane yield in the subtropical conditions of the northwestern Paraná region using climatic and soil water storage variables. Observed yield data was used from experiments conducted at the Experimental Station of the Sugarcane Genetic Improvement Program of the Universidade Federal do Paraná. The sugarcane varieties RB72454, RB867515, RB966928, and RB036066 were analyzed in the 1998–2006, 2008, 2018 and 2019 harvest years. Stepwise multiple linear regression analysis with repeated cross-validation was developed to estimate sugarcane yield given climate and soil water storage variables for crop growth phases. The accumulated degree days in Phases I and II and soil water storage in Phase II of development significantly impacted sugarcane yield. The multiple linear regression model, with accumulated degree days and soil water storage in Phases I and II of development, successfully predicted sugarcane yield for analyzed varieties. Sugarcane production models like the one we developed can improve crop management for greater sustainability and climate change adaption in Brazil and other areas.

Keywords: agrometeorological modeling; multiple linear regression; statistical model; sugarcane; yield prediction

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1. Introduction

Brazil is the largest producer of sugarcane (*Saccharum* spp.) in the world. The estimated production for the 2021–2022 harvest is 592 million metric tons [1]. However, the volume of raw material harvested this year was 9.5% less than the preceding 2020–2021 harvest due to drought during the production cycle and low temperatures in June and July, including frosts in some production areas [1]. The estimated production of the crop in the South Region of Brazil is 31.9 million metric tons, which was 6.7% lower compared to the previous year's harvest [1]. Climatic conditions during the sugarcane production cycle interferes with production. The identification of climate and soil factors that have a significant effect on the yield of sugarcane is fundamental to predicting production, successfully managing, selecting varieties, and suggesting alternatives for genetic improvement of the crop [2,3].

Sugarcane is a perennial crop, and its development is influenced by edaphoclimatic conditions [4,5]. Sugarcane production in Brazil expanded from 2000 to 2013; however, 88% of the increase was due to increase in production area and only 12% occurred due to increased productivity [6]. More than 90% of all sugarcane is grown without irrigation in Brazil, so the crop depends on rainfall to meet the sugarcane's water demand during growth, development, and production [6].

The availability of water in the soil during the vegetative growth phase is essential for sugarcane to express its productive potential, being the period in which the greatest water demand of the crop occurs [7,8]. Sugarcane stalk yields were 140% higher when grown under full irrigation compared to rain-fed situations, due to adequate water availability throughout the growth period, which makes nutrients available for the roots [9]. Extreme air temperatures, water deficit or surplus, and nitrogen deficiency interfere with the efficiency of solar radiation use and canopy expansion of sugarcane and, consequently, cane yield [10]. Therefore, the availability of water in the soil and climatic factors, such as solar radiation, influence the physiological processes of sugarcane.

In this context, the development and use of predictive models provide interesting alternative to help understand the responses of various crops to different environmental conditions in which they are grown, as well as in estimating their productivity [2]. The development of multiple linear regression models allows the identification of the variables that most interfere with crop yield and their estimation. Agrometeorological models, using as input monthly data of air temperature, precipitation, water deficiency and surplus, potential and actual evapotranspiration, water storage in the soil, and incident, global solar irradiation from the previous year were used by researchers [11] to estimate the sugarcane yields and quality. These yields were measured in metric tons per hectare, while sugarcane quality was measured as total recoverable sugar.

Multivariate regression models are an alternative to identify the variables that most influence sugarcane yield [11–13]. Multiple linear regression models estimating sugarcane yields with multiple variables have shown adequate performance. For example, precipitation, degree days, and negative degree days of the five months prior to harvest were used in multiple linear regression analysis to predict sugarcane yield [12]. Another multiple linear regression analysis verified the influence of climatic variables and available water in the soil on sugarcane productivity during El Niño and La Niña events in the state of Paraná during the summer, fall, winter, and spring [13].

Several researchers have sought to improve the genetics and productivity of sugarcane at the Experimental Station of the Sugarcane Genetic Improvement Program (PMG-CA) at the Federal University of Paraná (UFPR) as well as at the Interuniversity Network for the Development of Sugarcane Energy (RISESA) in Brazil [14,15]. Obtaining information on sugarcane yield in relation to soil and climate variables in long-term experiments can support sustainable agricultural management practices to ensure the growth, development, and production of sugarcane. In view of the context presented, the goal of the present study was to develop growth-stage (phenological phases I, II, and III) specific crop production models in order to better estimate sugarcane yield under subtropical soil and climate conditions. In order to achieve this goal, our research objectives were to (1) develop such growth-stage specific regression models for sugarcane specifically using climatic and soil water storage variables and to (2) validate our regression models with long-term sugarcane production data collected at PMGCA in Brazil.

2. Materials and Methods

2.1. Study Location and Agrometerological Data

Our research was developed in the Laboratory of Modeling of Agricultural Systems (LAMOSA) at the Setor de Ciências Agrárias (SCA) at the Universidade Federal do Paraná (UFPR). Analyses were carried out with crop data from experiments conducted at the Experimental Station of the Sugarcane Genetic Improvement Program (PMGCA) at UFPR and at the Interuniversity Network for the Development of Sugarcane Energy (a.k.a., RIDESA). The PMGCA is located at 22°58′ south latitude, 52°28′ west longitude and is at 470 m of average altitude in the municipality of Paranavaí, in the northwest region of the state of Paraná, Brazil. The climate of the region according to the Köppen classification is Cfa (subtropical climate), with average annual air temperature between 22.1 and 23 °C with average annual precipitation between 1400 and 1600 mm [16]. The agrometeorological weather station data used was obtained from the Paraná Rural Development Institute located in Paranavaí, Paraná state, Brazil for the period 1997 to 2019. Weather station variables used for modeling were incident solar radiation (Rs) measured in megajoules (MJ) per square meter (m^2) per day, rainfall (R) in millimeters, maximum temperature (T_{max}), minimum temperature (T_{min}), and average temperature (T_{avg}) all measured in °C, relative humidity (RH) as a percent (%), as well as wind speed (u) in meters per second [17].

2.2. Sugarcane Data

The observed sugarcane yields measure in metric tons per hectare were obtained from experiments conducted in the area of the Paranavaí Experiment Station, RIDESA, for the first ratoon cane crops (Table 1). Sugarcane yield data was available for the years 1998 to 2006, 2008, 2018, and 2019. The experimental station's experiments involved genetic improvement of sugarcane. From 1999 to 2005, experiments were conducted with other varieties. In this experimental area, sugarcane improvement research has historically been conducted and sugarcane varieties are grown in-field for evaluation. Sugarcane is typically planted in July with annual harvesting over a few years. Sugarcane harvesting in these experiments is done manually and without burning prior to harvest. Harvesting without burning leaves plant residues on the soil as straw and can improve yield and sugar content under conditions of water deficiency [18].

Table 1. Sugarcane yield measured in metric tons (t) of thatch per hectare (ha) for the varieties RB72454, RB867515, RB966928, and RB036066 from the Interuniversity Network for the Development of Sugarcane Energy in Paranavaí, Paraná state, Brazil [19].

	Cultivar's Observed Sugarcane Yield (t/ha)				
Year	**RB72454**	**RB867515**	**RB966928**	**RB036066**	**Average**
1998	130.604	-	-	-	130.604
1999	130.163	-	-	-	130.163
2000	98.988	-	-	-	98.988
2001	140.830	-	-	-	140.830
2002	127.940	-	-	-	127.940
2003	115.794	-	-	-	115.794
2004	141.600	99.304	113.417	-	118.107
2005	65.997	98.910	107.333	-	90.747
2006	164.190	134.173	-	-	149.182
2008	67.917	-	-	-	67.917
2018	-	80.715	152.570	101.533	111.606
2019	-	91.468	105.792	85.608	94.289

2.3. Adjustment of the Multiple Linear Regression Model

Multiple linear regression analyses using the stepwise method were carried out specifying sugarcane yield as the dependent variable in the models. Several independent variables were tested for use in our multiple linear regression models. These variables included soil water storage (SWS) to a depth of 0.6 m down in the soil profile. SWS is measured in centimeters. Weather station data used in regression models were reference evapotranspiration (ET) and daily rainfall (R) measured in millimeters per day, average relative humidity (RH) as a percentage (%), and incident solar radiation (R_s) and radiation balance at the surface (R_n), both measured in megajoules (MJ) per square meter (m^2) per day. Temperature (°C) variables included daily maximum (T_{max}), minimum (T_{min}), and average (T_{avg}) air temperatures as well as accumulated degree days (ADD). Total values were used for R and ADD, while median values were used for SWS, ET, RH, Rn, Rs, T_{max},

T_{min}, and T_{avg}). Median values were used since some variables (SWS, R, ADD, Rs, Rn) did not show normal distribution.

Sugarcane yields were modeled for three different phenological phases of ratoon sugarcane [20]. Phase I runs from July to October for a total of 93 days when sprouting and intense tillering occur. Phase II goes from October through March over 160 days where sugarcane has growth in stature. Phase III is the last phase running from March to July over 112 days where there is decrease in growth and accumulation of sucrose.

Soil water storage was simulated with the HYDRUS-1D software where HYDRUS numerically solves Richards' equation for water flow in saturated and unsaturated media [21]. The van Genuchten–Mualem model [22] was incorporated into HYDRUS to determine the relationship between hydraulic conductivity, volumetric moisture, and soil matric potential. The meteorological variables that were inputted into HYDRUS were rainfall, incident solar radiation, maximum and minimum air temperature, relative humidity, and wind speed. Reference evapotranspiration was calculated with the Penman–Montheith equation [23], which was incorporated into the program.

The accumulated degree days was calculated as the sum of degree days (*DD*) during the crop cycle according to past research [24]. The basal temperatures were considered equal to 19.0 °C, 23.5 °C, and 18.5 °C in sugarcane development stages I, II, and III, respectively The *DD* for these three stages are specified as:

$$DD = (T_{ni} - Tb_i) + \frac{(T_{xi} - T_{ni})}{2} \; for \; T_{ni} > Tb_i \tag{1}$$

$$DD = \frac{(T_{xi} - Tb_i)^2}{2 \cdot (T_{xi} - T_{ni})} \; for \; T_{ni} < Tb_i \tag{2}$$

$$DD = 0 \; for \; T_{xi} < Tb_i \tag{3}$$

where Tb_i is the lower base temperature of the crop, T_{xi} is maximum temperature of the *i*th day, and T_{ni} is minimum temperature of the *i*th day, all measured in °C.

2.4. Statistical Analyses

The associations between observed (Y) and estimated ($\hat{Y}$) values of sugarcane yield were evaluated with the error and coefficients of determination, calculated in the R software package, version 4.1.0 [25]. These associations included the mean absolute error (*MAE*) and the root mean square error (*RMSE*) measured in metric tons per hectare, and the coefficient of determination (R^2) which is dimensionless:

$$MAE = \frac{\sum_{i=1}^{n} |\hat{Y}_i - Y_i|}{n} \tag{4}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (\hat{Y}_i - Y_i)^2}{n}} \tag{5}$$

$$R^2 = \frac{(\sum_{i=1}^{n} (\hat{Y}_i - \overline{Y})\,(Y_i - \overline{Y}))^2}{(\sum_{i=1}^{n} (\hat{Y}_i - \overline{Y})^2)\,(\sum_{i=1}^{n} (Y_i - \overline{Y})^2)} \tag{6}$$

where $\hat{Y}_i$ is the *i*th value of the estimated variable, Y_i is the *i*th value of the observed variable, n equals the number of observed data points, and $\overline{Y}$ is the mean of the values of the observed variable. Note that *MAE* and *RMSE* values equal or close to zero indicate perfect fit to the data [26].

Multiple linear regression analyses were developed with the stepwise method and repeated cross-validation for 3 repetitions with k-fold (K independent groups) equal to 5. The stepwise method is used to select the best subset of variables that results in the model with the lowest cross-validation prediction error [27]. In the k-fold cross-validation method the data is randomly divided into k groups of equal size, uses "k − 1" groups for model fitting and the first group for validation, The process is repeated k times, with a different group being used for validation. The validation error is calculated with the average of the testing errors [27]. The samples were divided into 70% for parameterization and 30% for validation, using the caret and leaps packages of R based on the methodology from previous studies [28,29].

Other statistical tests were used such as analysis of variance, Shapiro–Wilk test for normality, test for multicollinearity using the variance inflation factor, and the Breusch–Pagan test for homoscedasticity. The statistical performance of multiple linear regression models and independent variable coefficients were evaluated using a confidence level of $\alpha < 0.05$. Regression models estimated sugarcane yields where were then compared to observed yield data from field experiments at the Experimental Station of the Sugarcane Genetic Improvement Program at the Universidade Federal do Paraná in Paraná state, Brazil. This contrast regressed observed yields against regression estimated yields where perfect fit of data ($R^2 = 1$) would have coordinates all fall on a positively sloped 45-degree angle line from the origin. Regression models were run in R [25].

3. Results

3.1. Agrometerological Data

The trend of climatic variables and soil water storage in the phenological phases of sugarcane and years used in the multiple linear regression analysis is summarized in Figures A1–A10. The variables for soil water storage (SWS), evapotranspiration (ET), solar radiation (R_s), surface radiation balance (R_n), average daily rainfall (R), maximum temperature (T_{max}), minimum temperature (T_{min}), and average temperature (T_{avg}) showed higher magnitudes in Phase II during sugarcane development. The highest sugarcane yields are typically associated with high average temperatures and high and uniform precipitation during the full vegetative growth phase [8]. In our study, the highest average air temperatures and rainfall coincided with Phase II of sugarcane stalk growth. The only exception was in 2004 where for rainfall during Phase II was lower than rainfall in Phase III.

The sugarcane crop cycle should coincide with ideal weather conditions [7] such as water demand and availability. Prior research found daily reference evapotranspiration of 5.24 ± 1.27 mm per day during the vegetative growth phase of sugarcane, a period in which the highest water demand of sugarcane variety RB867515 occurred in the microregion of Teresina, Piauí state, Brazil [7]. In the climatic conditions of Paranavaí, Paraná state, Brazil where the experimental data that we used were measured, the highest reference evapotranspiration (ET) was also observed in Phase II of sugarcane development. Rainfall irregularities in a tropical climate can provide distinct responses in the development and productivity of sugarcane varieties in crop cycles such as those for the varieties RB93509 and RB931003 in the Coastal Tablelands region of Alagoas in northeastern Brazil, where rainfall was also irregular [30].

3.2. Multiple Linear Regressions

The root mean square error (RMSE) was used to select the optimal model during the multiple linear regression analyses with repeated cross-validation. The lowest RMSE corresponded to the model with two predictors (Figure 1). The accumulated degree days (ADD, °C) and soil water storage (SWS, centimeters) in Phases I and II of sugarcane development constituted the best model fit with two predictors (Figure 2). The regression model coefficients of ADD for sugarcane growth Phase I and SWS for growth Phase II showed statistical significance ($p < 0.05$) (Table 2).

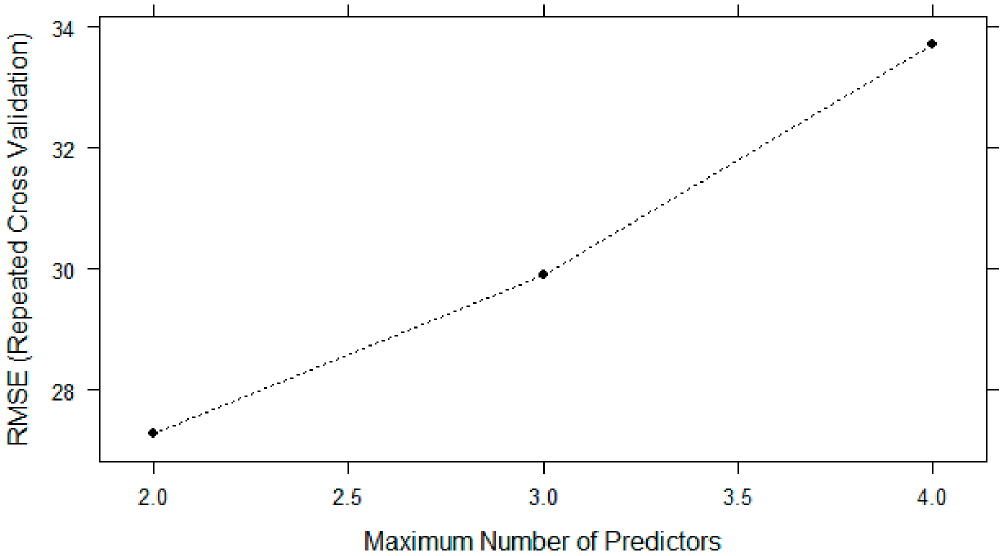

Figure 1. RMSE of repeated cross-validation to select the maximum number of predictors for multiple linear regression models of sugarcane yield estimation (TCH, tons of stalk per hectare), of ratoon cane, varieties RB72454, RB867515, RB966928, and RB036066.

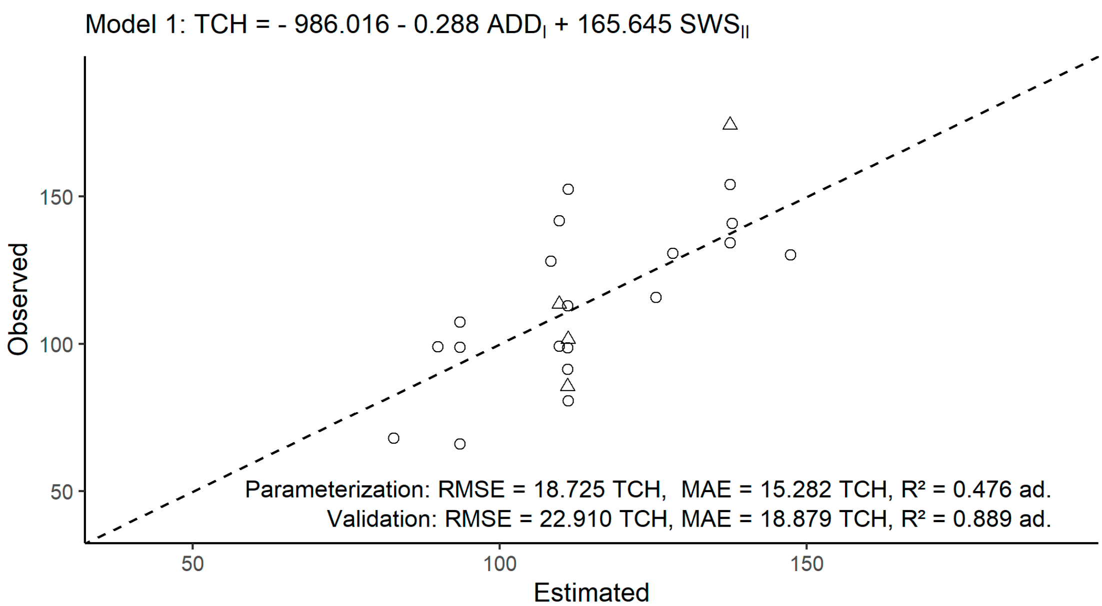

Figure 2. Parameterization and validation of the multiple linear regression model for estimating yield (TCH in metric tons of stalk per hectare) of ratoon cane, varieties RB72454, RB867515, RB966928, and RB036066 (O: parameterization and Δ: validation).

The coefficient of determination (R^2) explained 48% and 89% of the variation in sugarcane yield during model parameterization and validation, respectively. Varietal difference also interfered in the analyses, similar to prior research [31]. In our study, the sugarcane cultivar RB72454 had good agricultural productivity in any type of soil with medium maturity and high sucrose content. This cultivar was grown at the research site from 1998 to 2008. The second, third, and fourth sugarcane cultivars have been grown more recently in 2018 and 2019. The second variety evaluated was RB867515, which had high sucrose content and high agricultural productivity and is recommended for areas with low fertility and sandy and water-constrained soils. The third variety was RB966928, with high agricultural production, early to medium maturity, medium sucrose content, and a high degree of resistance to major diseases. Finally, the RB036066 sugarcane cultivar had high agricultural production, medium maturity, and wide adaptability and production stability. In the multiple linear regression analysis with repeated cross-validation for variety RB72454, the lowest RMSE also corresponded to the model with two predictors (Figure 3). The multiple linear regression analysis was performed only for variety RB72454, due to the greater number of 11 observations of sugarcane yield to allow for the parameterization and validation processes to be performed (Table 1).

Table 2. Multiple linear regression coefficients fitted to sugarcane yield (metric tons per hectare) for varieties RB72454, RB867515, RB966928, and RB036066, in the municipality of Paranavaí, northwestern region of Paraná State.

Coefficient [1]	Estimated	Standardized Estimated	Error [2]	t [3]	Pr(>∣t∣) [4]	$R^2_{ajust.}$ [5]
α	−986.016	∣0.000∣	412.180	−2.392	0.029 *	——
ADD_I	−0.288	∣−0.536∣	0.098	−2.928	0.010 *	0.410
SWS_{II}	165.645	∣0.524∣	57.961	2.858	0.011 *	——

[1] α is the regression coefficient, which represents the intercept; ADD_I is accumulated degree days in Phase I (°C); SWS_{II} is soil water storage up to 60 cm in Phase II. [2] Error is standard error (variable unit). [3] The t is the student's *t*-test values area dimensionless. [4] Pr(>∣t∣) is significance probability; * significant at 5% probability. [5] $R^2_{ajust.}$ is the adjusted coefficient of determination which is dimensionless. The *p*-value = 0.00572 is for the F-statistic.

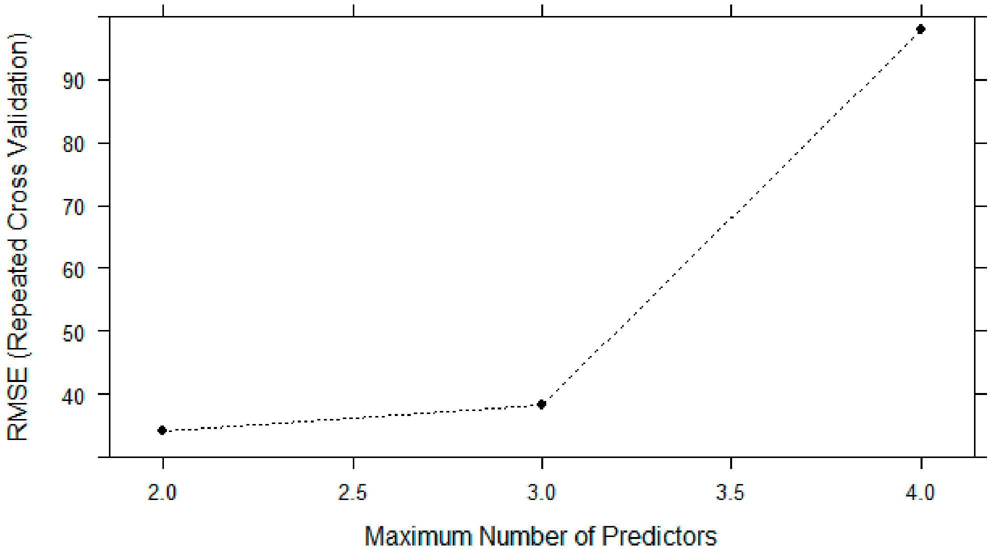

Figure 3. RMSE of repeated cross-validation to select the maximum number of predictors of multiple linear regression models for estimating yield (metric tons of stalk per hectare) of ratoon cane, variety RB72454.

The variables accumulated degree days (ADD_{II}) and soil water storage (SWS_{II}) in phenological phase II of ratoon cane were selected in the analysis and constituted the best model with two predictors for variety RB72454 (Figure 4). The regression coefficients of variables ADD_{II} and SWS_{II} showed statistical significance ($p < 0.05$) in the multiple linear regression model (Table 3).

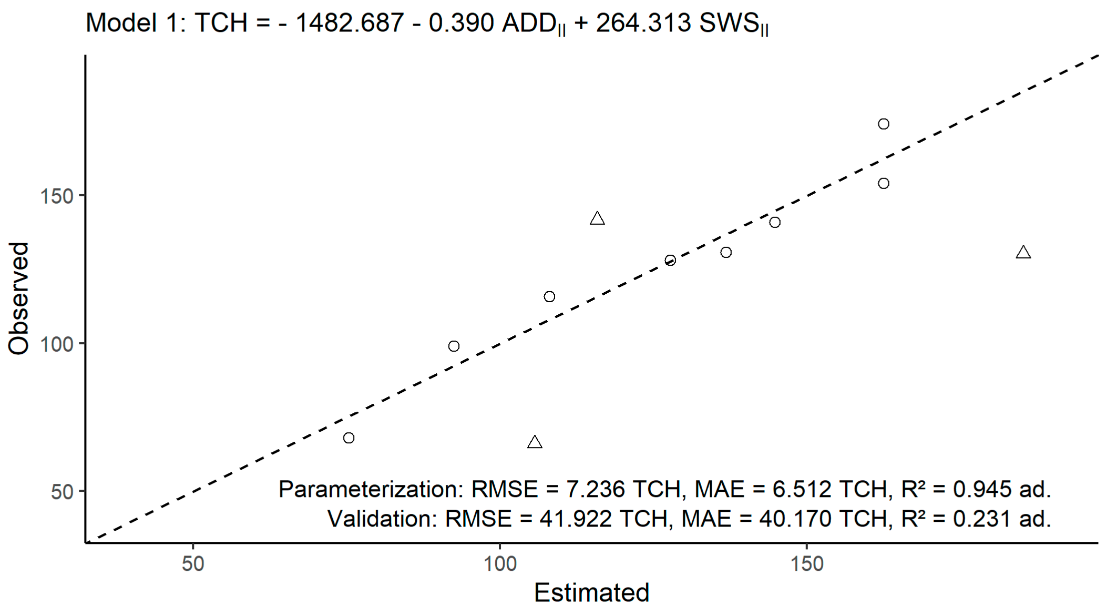

Figure 4. Parameterization and validation of the multiple linear regression model for estimating yield (TCH, tons of stalk per hectare) of ratoon cane, for the variety RB72454 (O: parameterization and Δ: validation).

Table 3. Multiple linear regression coefficients fitted to sugarcane yield (metric tons of per hectare) for variety RB72454 in the municipality of Paranavaí, northwestern region of Paraná State.

Coefficient [1]	Estimated	Standardized Estimated	Error [2]	t [3]	Pr(>∣t∣) [4]	$R^2_{ajust.}$ [5]
α	−1482.687	∣0.000∣	345.400	−4.292	0.008 *	——
ADD_{II}	−0.390	∣−0.713∣	0.058	−6.746	0.001 *	0.922
SWS_{II}	264.313	∣0.593∣	47.120	5.610	0.002 *	——

[1] The α is the regression coefficient, which represents the intercept; ADD_{II} is the accumulated degree days (°C), in Phase II; SWS_{II} is water storage in the soil up to 60 cm in Phase II. [2] Error is the standard error (unit of the variable). [3] The t is the student's *t*-test values (dimensionless). [4] Pr(>∣t∣) is the significance probability; * significant at 5% probability. [5] $R^2_{ajust.}$ Is the adjusted coefficient of determination, which is dimensionless. The *p*-value = 0.0007204 is for the F-statistic.

The coefficient of determination (R^2) explained 95% and 23% of the yield variation of variety RB72454 in the parameterization and validation of the model, respectively. The model fitted for variety RB72454 during validation showed the highest root mean square error (RMSE) and mean absolute error (MAE) and least explained variation. However, the effect of the selected variables should be considered due to statistical significance [12]. The climatic variations during the analyzed years is a factor that interfered in the explained variation of the model for variety RB72454 (Pr(>F) < 0.01; Figures A1–A10), as well as other factors that were not considered such as diseases and pests.

The accumulated degree days (ADD_{II}) and soil water storage (SWS_{II}) during Phase II of sugarcane development had an influence on the yield of sugarcane variety RB72454. The accumulated degree days in Phase I (ADD_I) and the soil water storage in Phase II (SWS_{II}) had significant effect on the yield of all four sugarcane varieties RB72454, RB867515, RB966928, and RB036066 under the climatic conditions in Paranavaí in Paraná state, Brazil. The identification of climate and soil variables that influence sugarcane yield is indispensable for complex models using a large number of parameters. Crop growth models [2] are fundamental for genetic improvement and identifying drivers for incremental improvements in crop yield. The results obtained in the experiments developed at the Experimental Station of the Sugarcane Genetic Improvement Program at the Universidade Federal do Paraná and at the Interuniversity Network for the Development of Sugarcane Energy can be references for future agricultural planning of sugarcane.

Past research has found that the variables selected in sugarcane modeling suggest that precipitation in the first, second, fourth, and fifth months and degree days in the fourth month prior to harvest had a significant effect on sugarcane yield during the 1999–2000, 2000–2001, and 2001–2002 harvests in the municipality of Pontal, São Paulo [12]. Precipitation was the variable with the most impact on sugarcane yield prediction models, confirming the importance of soil moisture for sugarcane production. Water stress during sugarcane crop development restricts physiological processes, such as its cell division and elongation, consequently reducing aboveground dry biomass [32]. Under severe water stress conditions such as between $-1500 < \psi < -1100$ kilopascals (kPa) measured with the weighing method measuring volumetric moisture versus matric potential, the daily transpiration rate of sugarcane was reduced by approximately 73% compared to plants grown under full water availability. With severe water stress and high values of global solar radiation, leaf temperature reached up to 6.6 °C above air temperature [33].

Research results reaffirm the importance of air temperature and soil water availability for sugarcane yield. For example, the average minimum temperature in spring, sum of precipitation in winter, sum of excess soil water in fall and summer, and the sum of soil water deficiency during summer explained 98% of the variation in sugarcane average annual yields (adjusted $R^2 = 0.982$) in Paranavaí, Paraná state, Brazil [13]. The accumulated degree days is a parameter used in simulation models of both sugarcane growth and production [34] and variation of aerial dry matter accumulation [35]. The model established in our study using accumulated degree days and soil water storage confirmed the importance of both variables in determining sugarcane yields due to their influence on the growth and development of the crop.

The climatic variables and water storage in the soil during the development phases for sugarcane can be used to predict the sugarcane yields. It is important to analyze and build models for each sugarcane variety since sugarcane cultivars respond differently to climatic and soil conditions such as water deficit [36], full irrigation [9], and intercepted photosynthetic radiation [37]. The number of observations is also an important factor in proposing models that explain sugarcane yield. As verified in our study, the reduced number of observations for sugarcane varieties RB867515, RB966928, and RB036066 limited the parameterization and validation of each variety.

The magnitude of the explanatory variables used to constitute models also Influences the ability to predict sugarcane yield. Previous research was unable to establish a predictive model for sugarcane yields using rainfall, degree days, and negative degree days of the five months prior to harvest [12]. The inclusion of other months in the multiple regression analysis would be an alternative, especially for months of vegetative growth. However, with these variables, two models were established to predict sugarcane maturity. During the maturation phase of sugarcane, the most relevant variables were found to be soil moisture and air temperature, with synergistic effects of the combination of both of these factors [38]. Temperatures lower than 20°C decreased growth and increased sucrose accumulation [39,40]. Future research should focus on modeling morphological variables for sugarcane yield models such as dry mass of the plant area and roots, plant height, diameter, and leaf area in relation to climate and soil variables during the phenological phases of the crop. This will help to better understand and identify relevant variables that most interfere in or enhance the development of and, consequently, the yield of sugarcane.

4. Discussion

4.1. Application to Previous Sugarcane Modeling

Our development of a sugarcane growth-stage-specific yield model can be integrated into other models that are more process based and not growth stage specific. These process-based models include DSSAT-Canegro [41,42] and APSIM-Sugar [43,44], specifically for the APSIM-Sugar model's specifications for sugarcane plant transpiration efficiency and supply of water to plant roots [45]. Our results were consistent with other studies that have used these models to estimate sugarcane yields based off of historical yield data in the major production region for sugarcane in southeastern Brazil. For example, our sugarcane total yield range of 80 to 140 metric tons (t)/hectare (ha) (Figure 2) was similar to Marin et al. (2012) [41], who estimated yield ranges of 96 to 129 t/ha for mid-century forecasting. In drier regions of Brazil, sugarcane yields and simulated yields are lower. For example, Dias et al. (2019) [10] modeled sugarcane yields ranging from 40 to 70 t/ha for the northeastern Brazilian state of Piauí in the arid Caatinga biome.

4.2. Sustainable Agricultural Implications

The sustainability of sugarcane in Brazil has both short-term and long-term challenges. In the short run, this involves having the crop play a role in conservation of natural areas such as on-farm required reserves of natural vegetation as well rehabilitating degraded livestock pastures. In the long run, land conservation and preservation are also linked to climate change and reduction in national greenhouse gas (GHG) emissions. Better simulation models for sugarcane can help balance crop productivity with agro-environmental goals. These improved models also allow for better forecasting of both future climate change impacts on sugarcane productivity as well as evaluating current and future crop systems with lower GHG emissions.

Recent sugarcane expansion in Brazil has occurred, for the most part, on land that has already been deforested [46], for example, for the Cerrado savannah and Atlantic Forest biomes [47]. Therefore, improving productivity and sustainability in sugarcane has more indirect effects on land-use change since improving productivity potentially frees up land to grow other crops and agricultural plantings (e.g., reseeded pasture) that are more likely to be introduced following deforestation and native vegetation conversion to agriculture. Although sugarcane is typically established on land that has already been cleared, it is not clear if this would indirectly drive Amazon deforestation for extensive pastured beef cattle due to conversion of pasture to sugarcane further to the southeast of Brazil [48].

Among the main results of this study and our research [49], soil water storage (SWS) can be modified using soil management practices. Sandy soils present differences in water retention due to the particle size composition of the sand fraction, which is an inherent soil characteristic [50,51]; organic matter content [52,53]; as well as land use and management [54]. Sugarcane is more susceptible to water stress during drought due to its shallow root system. Sugarcane water stress is especially severe in sandy soils due to low soil water retention, high soil density, high hydraulic conductivity, and greater root length density and root volume in the upper soil (0 to 0.2 m) layer [51].

According to Cherubin et al., 2022, the crop residue left behind as a soil surface mulch after green harvest of sugarcane can improve moisture retention [55]. Sandy soils require more mulching for adequate soil health for higher yielding sugarcane crops compared to clayey soils [56]. Such crop residues increased root mass and productivity of sugarcane even during drought in a Latosol with a clayey texture in a subtropical climate when 10 t/ha was applied [57]. However, Gallo et al., 2023 [58] demonstrated with field-study validated geospatial modeling in southeastern São Paulo state that unless other soil conservation methods (e.g., reduced tillage, contours, and terraces) were used then straw could not be removed.

In order to improve the physical and hydric conditions of the soil, using sustainable management systems is recommended. Sustainable management practices include continuous harvest without burning and leaving crop residues such as straw on the soil surface following harvest [57]. Another sustainable practice is crop rotation where such crop diversification of agro-ecosystem species can boost soil organic matter and biological activity [59]. This can increase water retention in the soil and reduce compaction in sandy soils. Soil compaction in sandy soils occurs due to heavy and intense traffic during agricultural machinery operations, especially during harvest [60]. Sugarcane yields have declined over the past decade due to this soil compaction from heavy equipment used for green harvesting [55]. However, Souza et al. (2020) found no compaction in sandy soils for sugarcane in Paraíba state, Brazil [61].

Climate change is projected to have adverse impacts on Brazil's sugarcane industry. Duden et al., 2021 [62] used the PCR-GLOBWB spatial terrestrial hydrology model to predict water deficit especially in center-west Brazil with projected increased sugarcane production for ethanol over the next decade. In São Paulo state, the transition to green harvest from burning prior to harvest has resulted in reduction in both total and per hectare greenhouse gas (GHG) emissions attributed to burning, fuel and input use, as well as from sugarcane crop and processing residues [63]. The APSIM-Sugar model forecasts under both RCP8.5 (business as usual) and RCP4.5 (greenhouse gas emission reductions) suggest that rainfed sugarcane yields would decline compared to the past ~40 years due to water stress. Even irrigated yields showed slight decline, but these projected changes were highly variable toward the end-of-21st century [44].

In the face of climate change and intensive land use in conventional systems, the adoption of sustainable management systems is critical for sugarcane cultivation [56]. Sugarcane shows no economies of scale due to lower yields from more industrial harvesting for large-sized farms, so the most profitable farm size at this point is for medium-sized farms [64]. Ruan et al., 2018 [65] use the APSIM-Sugar model to predict sugarcane yields under future climate change with results that suggest future sugarcane yields could be higher in southern China. However, this is challenging since China is third in 2020 global sugarcane production behind Brazil and India at only 14.28% of Brazil's sugarcane production [66]. Therefore, the best opportunity to balance global sugar needs with environmental sustainability may very well rest with Brazil.

5. Conclusions

In the present study, we investigated the main climatic variables and soil water storage characteristics influential in the development phases for sugarcane. Phase I is the sprouting and intense tillering period. Phase II is where the sugarcane crops grows and increases in height. Finally, Phase III is where there is a reduction in growth accompanied by sucrose accumulation. These three phases of sugarcane growth can be separately modeled in order to predict the yield of sugarcane in a subtropical climate grown in sandy soil. The accumulated degree days in Phases I and II and the soil water storage in Phase II of development exerted significant effects on sugarcane yield. Our multiple linear regression model with accumulated degree days (ADD_I) and water storage in the soil (SWS_{II}) in Phases I and II of development allowed for improved predictive capacity of sugarcane yield for the varieties that we analyzed. The model uses data that can be obtained during the sugarcane growing cycle and is an alternative resource to support production decisions related to soil and sugarcane plant management. Our model can also help support the adoption of sustainable management of sugarcane as well as yield forecasting. Our sugarcane production models for these crop development phases can be integrated in the future with whole-growth-stage models such as DSSAT-Canegro and APSIM-Sugar, with calibration of the coefficients, in order to better model future sustainable agricultural pathways for sugarcane both in Brazil and more globally.

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Appendix A

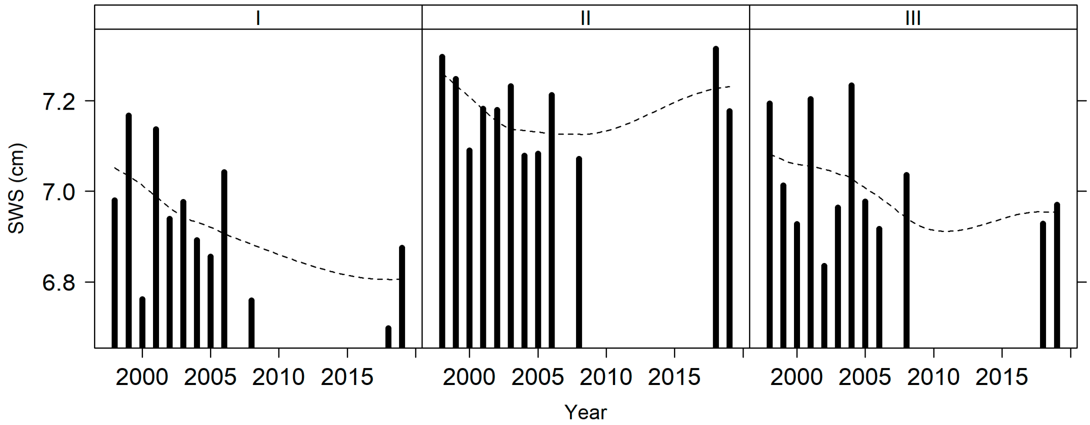

Figure A1. Climate variables for soil water storage (SWS in centimeters (cm)) in the sugarcane development phases I, II, and III (median) and cycle in the municipality of Paranavaí in the northwestern region of Paraná state, Brazil (dashed line corresponds to fitted trend).

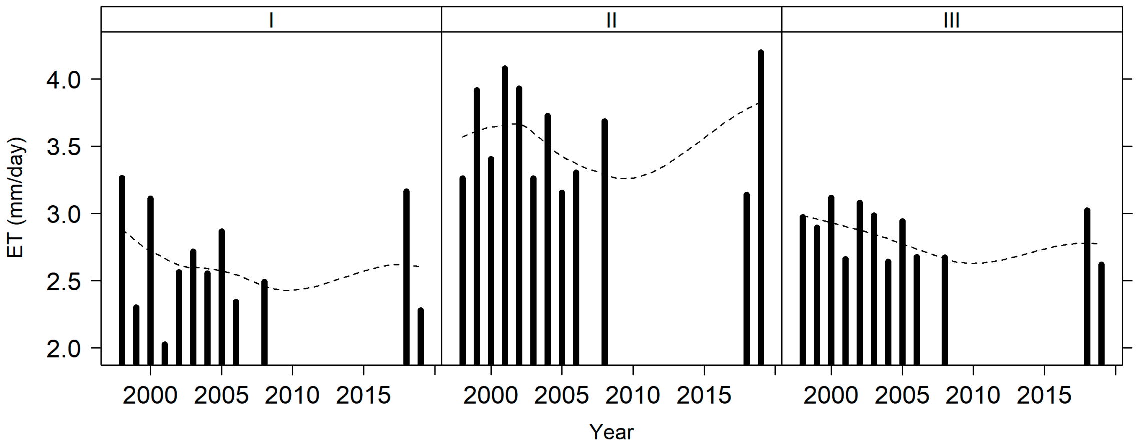

Figure A2. Climate variables for reference evapotranspiration (ET in millimeters (mm)/day) in the sugarcane development phases I, II, and III (median) and cycle in the municipality of Paranavaí in the northwestern region of Paraná state, Brazil (dashed line corresponds to fitted trend).

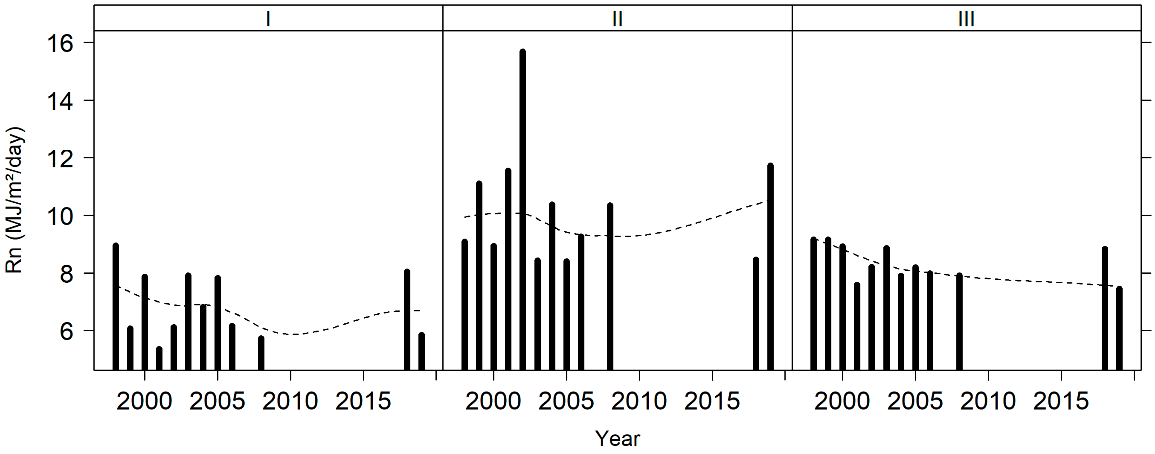

Figure A3. Climate variables for surface radiation balance (Rn in megajoules (MJ)/square meter (m^2)/day) in the sugarcane development phases I, II, and III (median) and cycle in the municipality of Paranavaí in the northwestern region of Paraná state, Brazil (dashed line corresponds to fitted trend).

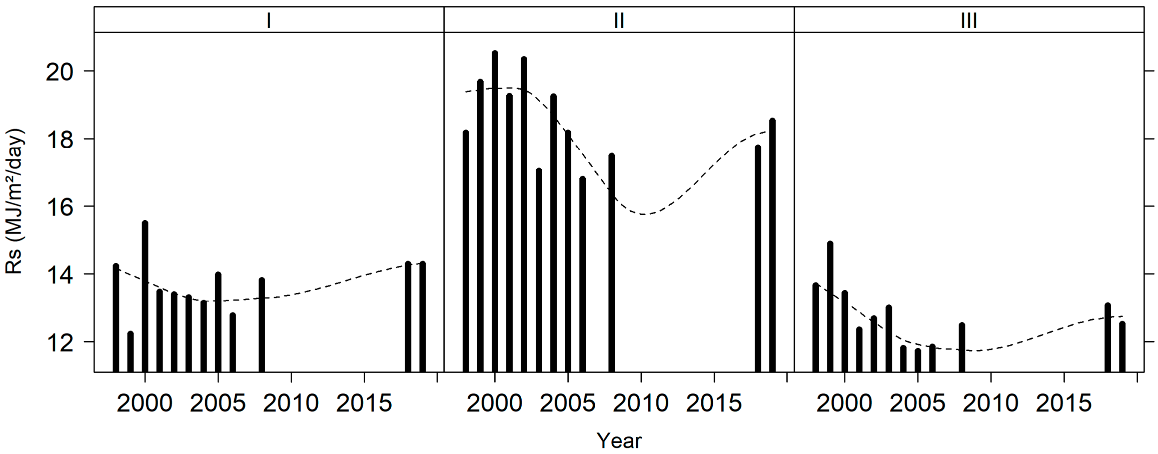

Figure A4. Climate variables for solar radiation (Rs in MJ/m^2/day) in the sugarcane development phases I, II, and III (median) and cycle in the municipality of Paranavaí in the northwestern region of Paraná state, Brazil (dashed line corresponds to fitted trend).

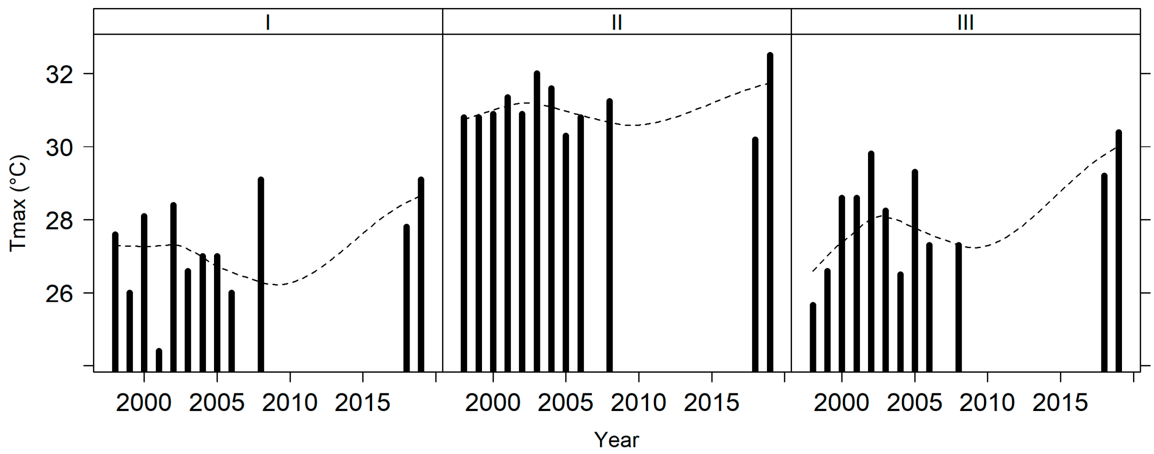

Figure A5. Climate variables for maximum temperature (Tmax in °C) in the sugarcane development phases I, II, and III (median) and cycle in the municipality of Paranavaí in the northwestern region of Paraná state, Brazil (dashed line corresponds to fitted trend).

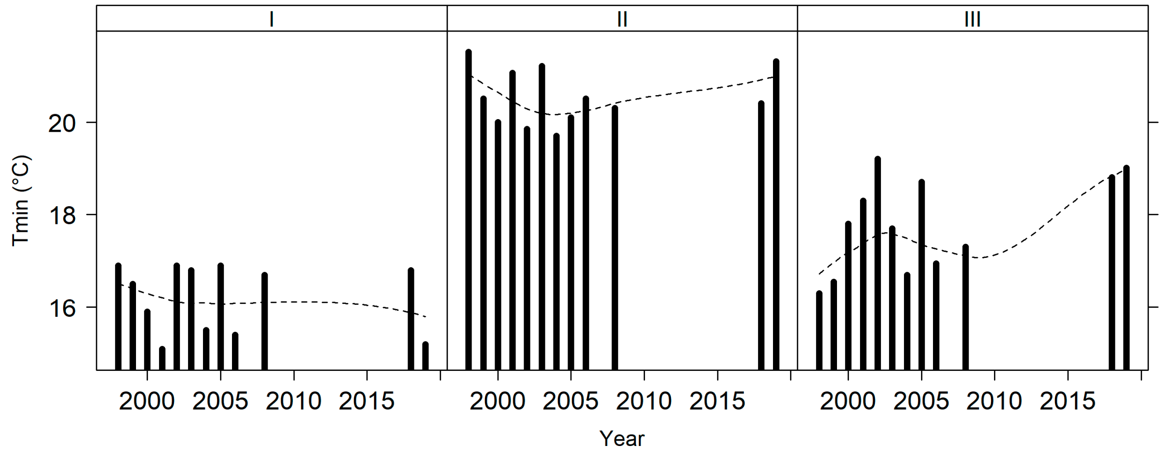

Figure A6. Climate variables for minimum temperature (Tmin in °C) in the sugarcane development phases I, II, and III (median) and cycle in the municipality of Paranavaí in the northwestern region of Paraná state, Brazil (dashed line corresponds to fitted trend).

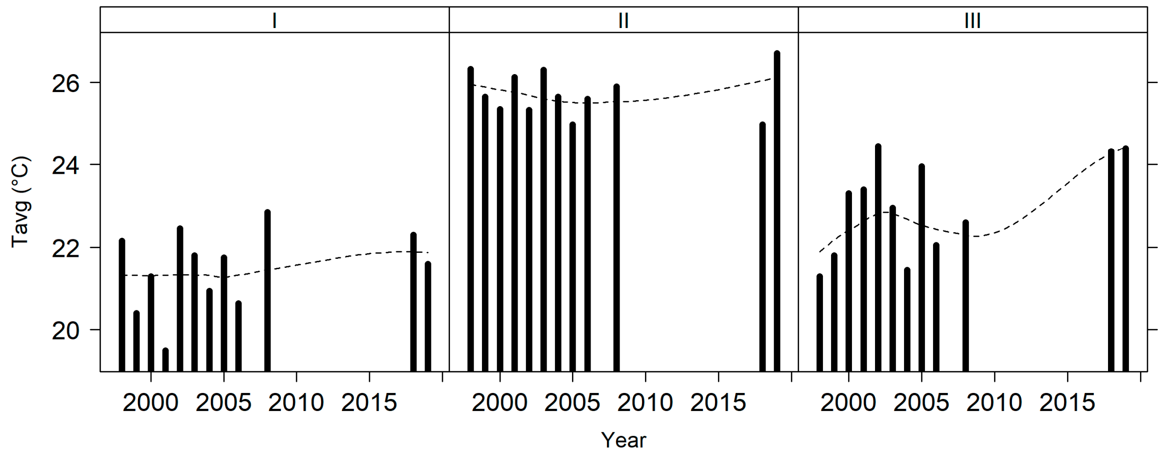

Figure A7. Climate variables for average temperature (Tavg in °C) in the sugarcane development phases I, II, and III (median) and cycle in the municipality of Paranavaí in the northwestern region of Paraná state, Brazil (dashed line corresponds to fitted trend).

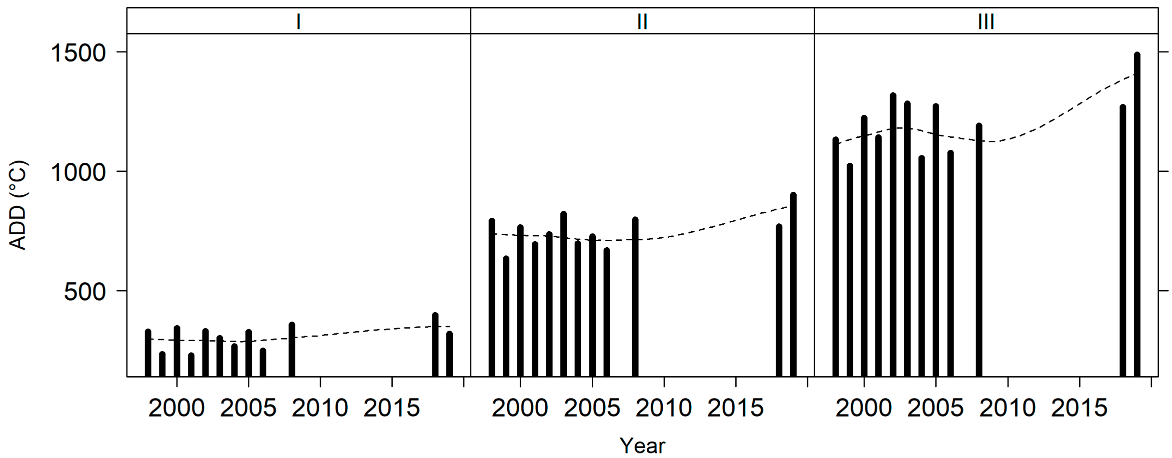

Figure A8. Climate variables for accumulated degree days (ADD in °C) in the sugarcane development phases I, II, and III (accumulated) and cycle in the municipality of Paranavaí in the northwestern region of Paraná state, Brazil (dashed line corresponds to fitted trend).

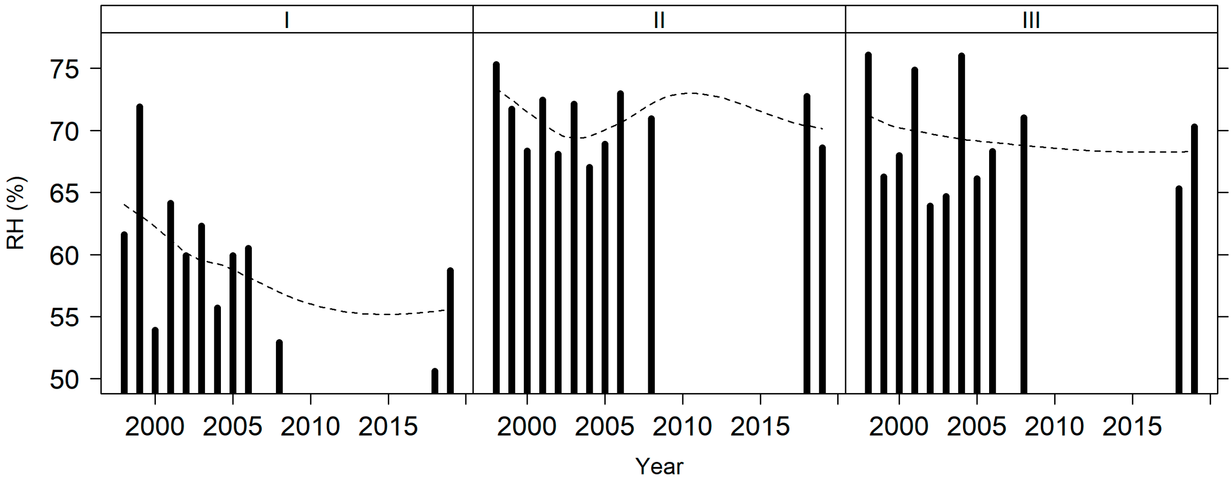

Figure A9. Climate variables for relative humidity (RH as %) in the sugarcane development phases I, II, and III (median) and cycle in the municipality of Paranavaí in the northwestern region of Paraná state, Brazil (dashed line corresponds to fitted trend).

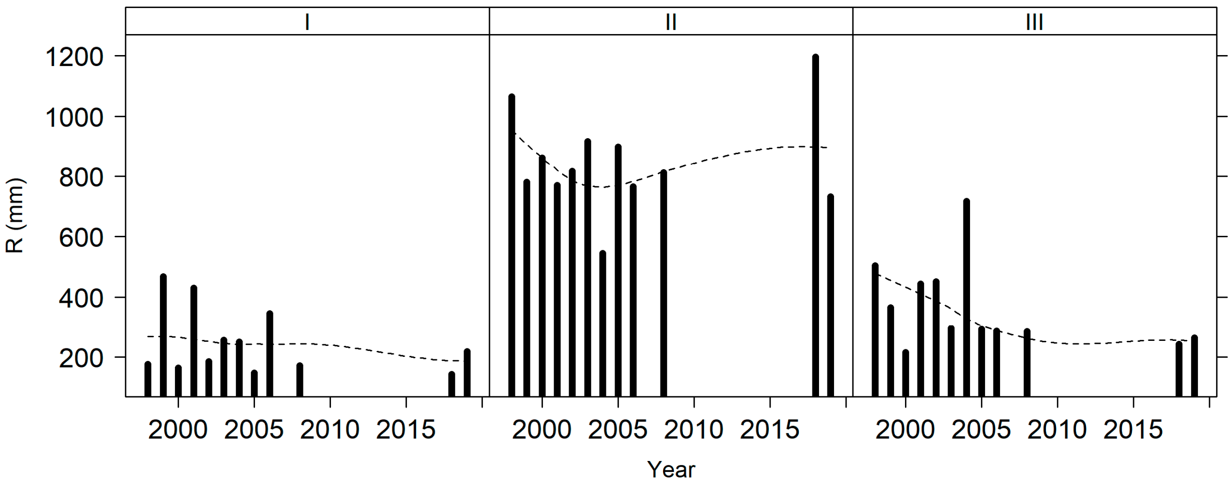

Figure A10. Climate variables for average daily rainfall (R in millimeters (mm)) in the sugarcane development phases I, II, and III (accumulated) and cycle in the municipality of Paranavaí in the northwestern region of Paraná state, Brazil (dashed line corresponds to fitted trend).

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