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RESEARCH

Using crop models, a decline factor, and a “multi-model” approach to estimate sugarcane yield compared to on-farm data

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Abstract

Sugarcane is an important crop in Brazilian agribusiness due to its diversified use. Crop forecast models are important tools for planning and making decisions regarding crop management. These models can be simple or complex, and choosing them will depend on the knowledge level of those using them. Thus, this study aimed to compare different methods for estimating sugarcane yield in three crop cycles. Data collection occurred in a sugarcane field in the municipality of Santo Antônio de Goiás, Brazil. The sugarcane variety evaluated was CTC-04. This variety was cultivated under dryland conditions, in cane plant, ratoon 1, and ratoon 2 cycles. Agrometeorological, biometric, and crop yield data were analyzed. Five crop models were used to estimate sugarcane yield: (i) FAO-Agroecological Zone (AEZ), (ii) agrometeorological-spectral (AEZs), (iii) Monteith (M), (iv) Scarpari (S), and (v) Martins and Landell (ML). Models AEZ, AEZs, M, and S showed average yield differences of about 15%, with the largest difference recorded by the ML model (39%). All models detected yield decline as a function of the number of harvests ($k_{dec} = -0.70$). The multi-model approach reduced the differences between estimated and actual values, especially for the combinations “AEZ + AEZs” and “AEZ + AEZs + M.” The present findings contribute to the investigation of different models with the potential to estimate sugarcane productivity.

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1 Introduction

More than a hundred countries around the world cultivate sugarcane, which is one of the most important crops due to the many applications of its products. These products include sugar, which is an important source of food energy, as well as ethanol (biofuel) and biomass (production of electricity and biogas), which are renewable energy sources (Ahorsu et al. 2018; Hughes et al. 2020; Bressanin et al. 2021; Soto et al. 2021).

Sugarcane is part of the history of Brazilian agribusiness production (Pelloso et al. 2020). Brazil is the world's largest producer; however, it did not occupy the top position in the yield ranking, remaining in the 24th (75.6 Mg ha^{-1}) place, with the highest averages being obtained by Peru (123.7 Mg ha^{-1}), Senegal (114.2 Mg ha^{-1}), and Guatemala (112.9 Mg ha^{-1}), and the global average being equal to 73 Mg ha^{-1} (FAO 2022).

In Brazil, the state of São Paulo is the largest producer (298.5 million Mg), followed by the state of Goiás (70.5 million Mg). São Paulo and Goiás showed similar average yield values for the 2021/2022 crop, equaling 70.9 and 73.2 Mg ha^{-1}, respectively (CONAB 2022). The state of Goiás has an average yield above the global average. However, Goiás is still behind the world's largest producers. Authors report that weather conditions, planting method, row spacing, and farm management practices are among the various factors influencing sugarcane growth and consequently affecting its yield (Garside and Bell 2009; Ruan et al. 2018; Chiluwal et al. 2018; Flack-Prain et al. 2021). The Goiás (Savanna biome) has a period of intense water deficit, which is the main cause of yield shortfalls (Monteiro and Sentelhas 2017; Casaroli et al. 2019, 2023; Caetano et al. 2021; Paixão et al. 2021). Irrigation is a viable alternative to mitigate water deficit effects, even if it meets only 50% of sugarcane water needs (Pereira et al. 2015; Araújo et al. 2016; Anjos et al. 2020; Antunes Júnior et al. 2021).

In most Brazilian crops, the ratoons are harvested four to five times. After 5 years, the sugarcane crop is replanted based on the yield level. The decline in sugarcane yield over successive ratoons restricts sugarcane production worldwide, which is mainly attributed to the quality of the crop management adopted (Bernardes et al. 2008; Ramburan 2015; Marin et al. 2019). The knowledge of sugarcane yield and of its evolution over time is essential in estimating the economic potential of the crop. As sugarcane incurs a high establishment cost (e.g., around 3500 US$ per hectare in relation to ratoon 1300 US$, in the Brazil (Pereira et al. 2015)), yields determine partly the crop profitability. Such a decline has already been reported for other perennial crops such as genus *Miscanthus*, a C4 tropical grass from the same tribe of the sugarcane (*Andropogoneae*) (Ferraro et al. 2009; Lesur et al. 2013). Analyzing a *Miscanthus giganteus* European long-term yield database allowed us to characterize that evolution through key variables such as the maximum yield, the duration to reach that maximum, and the decline rate. Maximum yields were found to be highly variable as well, and this variability was explained by a climatic influence. Model comparisons showed that yield evolution was best described when a decline hypothesis is included (Lesur et al. 2013). Thus, knowing this decline in yield at each harvest and its possible causes enables the producer and the entire production chain to plan.

Early warning of anomalous conditions on a regional and national scale allows stakeholders to secure imports and regulate the agricultural market (Atzberger 2013). Furthermore, sugar and ethanol supply chains involve distinct sectors at local (agriculture, transportation, milling, marketing), national, and global (energy, trade) levels. Therefore, in unfavorable conditions, clear, accurate, and transparent forecasts made available to the public and early warnings can mitigate price volatility, which often affects major food commodities because of unexpected production shortfalls and speculative actions (OCDE and FAO 2015).

Usually, experts conduct the forecast based on historical data regarding the growing area (soil and climate), cultivar characteristics, and crop management practices, mainly associated with pests, weeds, and disease control (Bocca et al. 2015). It is worth noting that monitoring sugarcane crops and human and financial resources is sometimes time-consuming. Significant sampling is difficult to perform in large extensions of cultivated areas, which can lead to sampling inefficiency and/or errors in crop forecasts (Leal et al. 2013; Kumar et al. 2017). Thus, it becomes feasible to use crop models that estimate crop yields. However, it is not always easy to choose the model because they have different complexity levels. Multivariate regression analyses are among the most straightforward and can have biometric data (Martins and Landell 1995) or meteorological data (Scarpari 2002) as input variables. More accurate models are based on biophysical processes. These models require a larger number of input variables, which makes them more complex. In this group, the agrometeorological model (Doorenbos and Kassam 1979), the agrometeorological-spectral model (Rudorff and Batista 1990), and the models based on remote sensing data sets (Monteith et al. 1972, 1977) stand out.

Despite their clear importance, isolated studies can be improved when worked in an integrated way, following a "multi-model" approach (Marin et al. 2015; Dias and Sentelhas 2017, 2018). These studies sometimes determine growth patterns of varieties or estimate yield from destructive biomass samples (Lauer 2002; Jane et al. 2020) and sometimes correlate agrometeorological and water variables to sugarcane yield (Basnayake et al. 2012; Caetano and Casaroli 2017; Monteiro and Sentelhas 2017; Culman et al. 2019; Caetano et al. 2021; Paixão et al. 2021; Swami et al. 2021). Therefore, based on the knowledge of the advantages and limitations of different models, producers can use one or more models for planning and monitoring their crops.

Accordingly, this study used parameterized literature and experimental data to compare five sugarcane yield estimation models that consider biometric, agrometeorological, and spectral data. Furthermore, this study aimed to identify the yield decline as a function of the number of harvests and to apply the "multi-model" approach to yield estimation.

2 Material and methods

2.1 Study site

The data were collected in the Louzandira farm, in Santo Antônio de Goiás city, Goiás State (16°28′12.11″ S; 49°21′9.47″ W; 780 m), Brazil, which consists of a production area with 106.45 ha, belonging to the CentroAlcool® mill (Fig. S1; see Supplementary Material). According to the Köppen climate classification, the climate in the city is Aw (tropical Savanna/megathermal) (Alvares et al. 2013). The rainfall regime is well defined, with a rainy season (October–April) and a dry season (May–September) and an annual average of 1525 mm (Jardim et al. 2023).

Sugarcane planting took place in April 2013 in a semi-mechanized way, with pre-sprouted seedlings and 1.5 m spacing. The planted variety was the CTC-4 (see its characteristics and representativeness in Supplementary Material). Evaluations comprised the cane plant (2013/2014), ratoon 1 (2014/2015), and ratoon 2 (2015/2016) cycles in rainfed cultivation.

The soil of the area under study was a dystrophic Red-Yellow Latosol (EMBRAPA 2018), corresponding to Ferralsols (WRB/FAO) or Oxisols (Soil Taxonomy), with medium texture: 27% clay, 13% silt, and 60% sand.

The authors emphasize that the climate and soil conditions in the municipality of Santo Antônio de Goiás were considered typical of the Brazilian Savanna biome (EMBRAPA 2020).

After soil chemical analysis (Table S1; see Supplementary Material), the soil was corrected with the application of limestone (4.0 Mg ha^{-1}) and gypsum (2.0 Mg ha^{-1}). Moreover, 120 kg ha^{-1} P_2O_5 were applied for fertilization, and 380 kg ha^{-1} of the formulated 18–00-27 (NPK) were applied as topdressing, repeating the latter applications in ratoon cycles 1 and 2. Weeds were controlled with the application of herbicides in the amounts recommended by the manufacturer. The CentroAlcool® mill carried out both the fertilization and the application of herbicides.

Five sampling points were demarcated in the cultivation area. These points were approximately 190 m apart, except for points 4 and 5, which were 450 m apart (Fig. S1; see Supplementary Material). Each point consisted of three plots formed by five crop rows (1.5 m spacing), with 10 linear meters in length (75 m^2). At each sampling point, the distance between the plots was ten crop rows, placed side by side.

2.2 Plant growth and yield

Biometric evaluations included nine plants per plot, three in each crop row, using the three central rows of the plot. In the 2013/2014 harvest, in the cane plant cycle, evaluations started on 05/20/2013 with 50 days after planting (DAP). In the 2014/2015 (ratoon 1) and 2015/2016 (ratoon 2) harvests, evaluations started at 66 and 53 days after cutting (DAC), respectively. The assessments were performed at non-equidistant intervals, ranging from 15 to 50 days, to ensure favorable field conditions for data collection (Table S2; see Supplementary Material).

The variables stalk height (H, m) and diameter (D, m), number of tillers per linear meter (T, number m^{-1}), leaf area (LA, m^2), and leaf area index (LAI, m^2 m^{-2}) were evaluated according to the methodology described in the supplementary material. The mill obtained the real yield (Yr, Mg ha^{-1}) and carried out the harvest separately in five smaller areas, which coincided with the experimental data collection points (Fig. S1, see Supplementary Material).

2.3 Agrometeorological data

Agrometeorological data were collected in an automatic weather station installed 7 km from the experimental area on a daily scale during the experimental period. The data concerned the following variables: maximum, minimum, and average air temperatures (°C), rainfall (mm), relative air humidity (%), wind speed at 2 m height (m s^{-1}), solar radiation, and net radiation (MJ m^{-2} day^{-1}). From meteorological data, the authors estimated reference evapotranspiration (ETo, mm day^{-1}) by the standard FAO Penman–Monteith method (Allen et al. 1998).

In addition, the authors determined degree-days (DD, °C day) throughout the sugarcane cycles by following the set of equations proposed by Ometto (1981), with lower basal temperature Tb = 16 °C and upper basal temperature TB = 42 °C (Bonnett 2013). For thermal time ($\sum$DD, °C day) determination, we used the sum of the degree-days during the phenological phases and for the cultivation cycles.

Sugarcane water balance (Thornthwaite and Mather 1955) was calculated daily, starting with planting and ending with harvesting the second-cut ratoon cane. For this, total available water (TAW, mm) and readily available water

(RAW, mm) were first determined (Eq. S3 and S4; see Supplementary Material). The main water input into the system was rainfall. Water output was governed by crop evapotranspiration (ETc, mm day^{-1}), which is the product between ETo and crop coefficient values (Kc), for each phase of sugarcane development, as well as for the different cultivation cycles (Table S3; see Supplementary Material).

2.4 Crop models

Five crop models were used to estimate sugarcane yield, being one based on biometric measurements (ML), two agrometeorological models (AEZ and S), one agrometeorological-spectral model (AEZs), and one morphophysiological-spectral model (M).

2.4.1 Model 1: FAO-Agroecological Zone (AEZ)

The Agroecological Zone model, described by the FAO (Food and Agriculture Organization), is a generic mathematical-physiological crop simulation model developed by Doorenbos and Kassam (1979), which estimates the potential (Yp) and achievable (Ya) yields of a crop using agrometeorological data. The potential yield (Yp) represents the maximum yield of a variety well adapted to environmental conditions, with no water, nutritional, or phytosanitary restrictions. On the other hand, the achievable yield (Ya), besides considering the determining factors (genotype, population, air temperature, solar irradiation, and photoperiod), is also influenced by the accumulated water deficit during the crop cycle. The AEZ model has been previously calibrated for sugarcane grown under Brazilian conditions (Marin and Carvalho 2012; Monteiro and Sentelhas 2014; Dias and Sentelhas 2017). Thus, some approaches and parameters followed the recommendations of Dias and Sentelhas (2017) and Monteiro and Sentelhas (2014) for the cane plant and ratoon cycles (Table S3; see Supplementary Material).

Potential yield (Yp, kg ha^{-1}) was estimated considering the interaction between crop photosynthesis patterns (C4), solar radiation, photoperiod, and air temperature during the cycle, according to Eq. 1 (Kassam 1977):

$$\mathrm{Yp} = \sum_{i=1}^{m} GP \times C_{\mathrm{LAI}} \times C_{\mathrm{R}} \times C_{\mathrm{H}} \times \left(1 - C_{\mathrm{W}}\right)^{-1} \quad (1)$$

where GP is the gross photosynthesis, which contemplates the dry mass gain per unit area per day (kg DM ha^{-1} day^{-1}), considering a standard crop, with leaf area index equal to five (see Gross photosynthesis in the Supplementary Material); C_{LAI} (Eq. 2) is the leaf area index (LAI) depletion coefficient, which assumes its maximum value of 0.5 when $LAI_{max} \geq 5$; and when $LAI_{max} < 5$ then:

$$C_{\mathrm{LAI}} = 0.0093 + 0.185 \times \mathrm{LAI}_{\max} - 0.0175 \times \mathrm{LAI}_{\max}^2 \quad (2)$$

This study used the LAI calibrations recommended by Monteiro and Sentelhas (2014) (Table S3; see Supplementary Material); C_R is the depletion coefficient associated with the maintenance respiration process as a function of air temperature ($C_R = 0.6$ for $T < 20$ °C and $C_R = 0.5$ for $T \geq 20$ °C); C_H and C_W are the harvest index and the water content of the harvested part of the plant, using values of 0.8 and 70%, respectively (Doorenbos and Kassam 1979; Dias and Sentelhas 2017); "i" is the day of the crop cycle, and "m" is the total days of the crop cycle from planting to harvest (cane plant = 546 days; ratoon = 362).

The achievable yield (Ya, kg ha^{-1}) was found by penalizing Yp with water deficit, which was obtained from the water deficit sensitivity coefficients (ky) for each developmental stage (Table S3; see Supplementary Material), according to Eq. 3:

$$\mathrm{Ya} = Y_{\mathrm{p}} \times \prod_{i=1}^{\mathrm{np}} \left\{ 1 - ky_{\mathrm{i}} \times \left(1 - \frac{\mathrm{ETa_i}}{\mathrm{ETc_i}} \right) \right\} \quad (3)$$

where ETa is the actual evapotranspiration (mm day^{-1}), ETc is the maximum crop evapotranspiration, "i" is the crop phase, and "np" is the total number of phases during the crop cycle. The water deficit was quantified using the ETa/ETc ratio obtained from the water balance.

2.4.2 Model 2: Agrometeorological-spectral (AEZS)

This model is based on the FAO-Agroecological Zone (AEZ) model and was described in FORTRAM language by Rudorff (1985). The model has shown relevant aspects for studies at regional scales due to the possibility of estimating the leaf area index (LAI) using remote sensing images (Rizzi and Rudorff 2007). Rizzi (2004) adjusted the input spectral variable in the AEZ model using the potential yield (Yp, kg ha^{-1}) given by Eq. 1, estimating the Fgc (growth compensation factor) parameter (Eq. 3), which is a multiplicative factor of the coefficients of respiration (C_R), agricultural productivity ($\mathrm{Fap} = C_H/[1 - C_W]$), of the duration in days of each phenological phase (Table S2, see Supplementary Material), and of gross photosynthesis (GP, see Supplementary Material).

The growth compensation factor (Fgc) independs on the crop type and is determined as a function of LAI_S (Eq. 4):

$$\mathrm{Fgc} = 0.515 - e^{(-0.664 - (0.515 \times \mathrm{LAI_S}))} \quad (4)$$

The spectral leaf area index (LAI_S) was estimated following the methodology suggested by Campbell and Norman et al. (1998) (Eq. 5):

$$\mathrm{LAI_S} = -2Ln(1 - \mathrm{Fc}) \quad (5)$$

where Fc is the land cover fraction (Choudhury et al. 1994), estimated from the NDVI (Normalized Difference Vegetation Index) values, for the 2013/2014, 2014/2015, and 2015/2016 crops, according to Eq. 6:

$$\mathrm{Fc} = 1 - \left(\frac{\mathrm{NDVI_M} - \mathrm{NDVI}}{\mathrm{NDVI_M} - \mathrm{NDVI_m}}\right)^{0.9} \tag{6}$$

where $\mathrm{NDVI_M}$ and $\mathrm{NDVI_m}$ are the maximum and minimum values of the image, and NDVI is the value of the pixel for which the Fc value is being calculated.

Table S4 and Fig. S2 (Supplementary Material) show the maximum LAI values estimated from the NDVI ($\mathrm{LAI_{MS}}$).

For estimating the leaf area index (LAI), based on NDVI, we used the satellite image dataset of surface reflectance from Landsat-8/OLI, with an acquisition interval of 16 days and spatial resolution of 30 m. Scenes were selected between the dates of sugarcane planting (cane plant: April/2013) and harvesting (ratoon 2: October/2016). For each scene, the pixels containing clouds and cloud shadows were eliminated. The NDVI was calculated using the red (B4) and near-infrared (B5) bands. Normalized Difference Vegetation Index (NDVI) images were used to determine the Fc images (Eq. 6), which generated the study area's average profile. All processing involved using the Google Earth Engine (GEE) platform.

2.4.3 Model 3: Monteith (M)

Dry matter production (DM, g m^{-2}) was based on the model proposed by Monteith (1972, 1977), which estimates DM from absorbed photosynthetically active radiation by plants (APAR, MJ m^{-2}) and solar radiation use efficiency (RUE, g MJ^{-1}) (Eq. 7):

$$\mathrm{DM} = \mathrm{APAR} \times \mathrm{RUE} \tag{7}$$

Absorbed photosynthetically active radiation (APAR) was estimated by the product of photosynthetically active radiation (PAR) and the fraction of PAR absorbed (f_{APAR}). At the same time, RUE was equal to 3.35 g MJ^{-1} (Heerden et al. 2010). Photosynthetically active radiation (PAR) was considered 0.5 of the global solar radiation (Rs) (Papaioannou et al. 1993; Zhu et al. 2017), and the values of f_{APAR} were determined by the equation proposed by Ahl et al. (2005) (Eq. 8):

$$f_{\mathrm{APAR}} = 1 - e^{(-k\mathrm{LAI})} \tag{8}$$

where k is the light extinction coefficient (Campbell and Norman 1998), considered equal to 0.58 for this study (Inman-Bamber 1994), and *LAI* is the leaf area index (LAI). Leaf area index was obtained using the NDVI (Normalized Difference Vegetation Index), derived from remote sensing (Pereira et al. 2016). Finally, sugarcane yield (Mg ha^{-1}) was obtained by DM (g m^{-2}), considering the water content of the harvested part of the plant to be 70% (Dias and Sentelhas 2017).

2.4.4 Model 4: Scarpari model (S)

Scarpari (2002) proposed an agroclimatic model to predict sugarcane stalk mass per hectare (Y_S, Mg ha^{-1}) as a function of the precipitation (P, mm) and degree days (DD, °C day) variables of the 5 months before harvest, adjusting the model for cane cycles of 1.5 years (18 months), or 1 year (12 months), according to Eqs. 9 and 10, respectively:

$$Y_S = 35.72306 + 0.57487 \times P_1 + 0.22957 \times P_2 + 0.29839 \times P_4 + 0.89310 \times P_5 - 0.34098 \times \sum \mathrm{DD}_4 \tag{9}$$

$$Y_S = 64.21145 + 0.27273 \times P_4 \tag{10}$$

where P_n is the precipitation of the "nth" month before harvest (mm), and $\sum \mathrm{DD}_n$ is the sum of degree days in the "nth" month before harvest (°C day). Day degree determinations vary according to the average air temperature and the crop's lower and upper basal temperatures (Ometto 1981).

2.4.5 Model 5: Martins and Landell (ML)

The model proposed by Martins and Landell (1995) estimates the sugarcane crop stalk fresh mass yield (Y_{ML}, Mg ha^{-1}) according to the expression (Eq. 11):

$$Y_{\mathrm{ML}} = D^2 \times NIT \times AHS \times \left(\frac{0.007854}{SBF}\right) \tag{11}$$

where D is stalk diameter (cm), *NIT* is the number of tillers per linear meter, *AHS* is the average height of stalks (cm), *SBF* is furrow spacing (1.5 m), and 0.007854 is the appropriate correction factor for sugarcane. According to the recommendations, the average data to be considered refer to one or more evaluations made from the 8th month after cutting or planting. For this study, the data matched assessments made after the 8th month after planting or cutting: from the 8th to the 18th assessment for cane plant; from the 13th to the 15th for ratoon 1; and from the 9th to the 11th for ratoon 2 (Table S2; see Supplementary Material).

2.5 Yield decline factor

Sugarcane yield is a function of crop management and the interaction between the genotype (plants) and the environment (climate and soil). Given that the models only estimate yield under optimal management conditions, yield decline may be a limiting variable for the performance of sugarcane models in commercial crops. An exponential decline in yield as a function of the number of harvests was adjusted for Brazilian cultivars (Bernardes et al. 2008) (Eq. 12):

$$Ye_{nh} = Ya_{1h} \times nh^{-k_{dec}} \tag{12}$$

where Ye_{nh} is the estimated current yield for a given harvest (Mg ha^{-1}), Ya_{1h} is the achievable yield at the first harvest, nh is the number of harvests, and k_{dec} is the yield decline factor. The yield decline factor (k_{dec}) was fitted to the experimental yield data obtained from the cane plant and ratoon cycles. After that, yields were estimated by the models considering the exponential decline factor.

2.6 Multi-model

Based on the yield data estimated by the crop models, a "multi-model" analysis was performed. This analysis involved obtaining averages of different combinations of the models used. Averages of 21 combinations were determined (Table 1).

For each crop cycle (cane plant, ratoon 1, and ratoon 2), these averages were compared to the real yield obtained by the mill (Yr), finding numerical (Δ, Mg ha^{-1}), and percentage (Δ%) differences and their standard deviations (SD). The relative Δ and SD values of the 21 combinations, ranging from 0–1, were obtained to indicate or reject one or more models. After that, the sums between Δ and SD (Δ + SD) were obtained, and relative values were also determined.

2.7 Statistical analysis

Regression analyses were applied between the observed and model-estimated values. Furthermore, the models were tested using statistical indexes, such as determination coefficients (R^2), bias or mean error (Bias), Pearson's "*r*" coefficient (*r*), mean absolute error (MAE), root mean square error (RMSE), agreement index "*d*" (Willmott et al. 1985), and method efficiency (EF).

3 Results

3.1 Biometric analysis

Sugarcane plant growth was observed as a function of the thermal sum, which accumulated in each phenological phase and cycle (Fig. S3, see Supplementary Material). All variables in all cycles had their observed values fitted to mathematical models of Sigmoid, Gaussian, exponential, or log-normal type, which obtained $R^2 > 0.90$ and significant parameters with $p < 0.001$ (Table S5; see Supplementary Material). Furthermore, these models generated excellent statistical indexes between the observed and estimated data (Fig. S4, S5, and S6; see Supplementary Material).

The maximum height (*H*) and diameter (*D*) values were obtained in the cane plant cycle ($H = 4.1$ m; $D = 0.0336$ m), in which the lowest standard deviations ($\sigma \pm 0.1343$ m and $\sigma \pm 0.0012$ m; respectively) were observed (Fig. S3a, b; see Supplementary Material).

The number of tillers per linear meter (*T*) showed decreasing trends throughout the cycle, with its highest values detected in the early stages. Regarding the crop cycles, the ratoon 1 cycle obtained the highest value (25.0 ± 1.8 tillers m^{-1}), followed by cane plant cycles (23.2 ± 1.4 tillers m^{-1}) and ratoon 2 (18.3 ± 2.2 tillers m^{-1}) (Fig. S3c; see Supplementary Material).

The maximum leaf area (LA) and the maximum leaf area index (LAI) were detected in ratoon cycle 1, equaling 11.5 ± 0.95 m^{-2} m^{-1} and 7.7 ± 0.63, respectively. The ratoon 2 cycle recorded intermediate values (LA = 11.2 ± 0.92 m^{-2} m^{-1}; LAI = 7.4 ± 0. 61), and the cane plant cycle showed the lowest averages (LA = 8.2 ± 0.47 m^{-2} m^{-1}; LAI = 5.5 ± 0.32) (Fig. S3d, e; see Supplementary Material). It is worth noting that, while behaving the same, the LAI values obtained by satellite images were lower than the experimental data, especially at the end of the cycle (Fig. S2, see Supplementary Material).

Table 1 Number of crop model combinations used to obtain yield averages for cane plant, ratoon 1, and ratoon 2. AEZ, FAO-Agroecological Zone model; AEZs, FAO-Agroecological-spectral model; M, Monteith model; S, Scarpari model; ML, Martins and Landell model

Model combinations													
1	AEZ	AEZs	8	M	S		15	AEZs	S	ML		
2	AEZ	M	9	M	ML		16	M	S	ML		
3	AEZ	S	10	S	ML		17	AEZ	AEZs	M	S	
4	AEZ	ML	11	AEZ	AEZs	M	18	AEZ	M	S	ML	
5	AEZs	M	12	AEZ	M	S	19	AEZ	AEZs	S	ML	
6	AEZs	S	13	AEZ	S	ML	20	AEZ	AEZs	M	ML	
7	AEZs	ML	14	AEZs	M	S	21	AEZ	AEZs	M	S	ML

3.2 Agrometeorological data

The maximum, minimum, and average air temperature averages were 29.6 °C, 18.1 °C, and 23.9 °C within the three crop cycles (cane plant, ratoon 1, and ratoon 2). The average temperatures in the cane plant, ratoon 1, and ratoon 2 cycles were 3.1%, 4.3%, and 6.3% higher than the city's climate average (1986–2016), respectively (Fig. S7a; see Supplementary Material).

The average relative humidity (RH) values in all three cycles were between 60 and 65%. However, at certain times during the cycle, RH values were $< 50\%$ (Fig. S7a; see Supplementary Material).

Cumulative precipitation values (R) resulted in 1923.6 mm (cane plant), 1390.2 mm (ratoon 1), and 1168.0 mm (ratoon 2), generating daily averages equal to 4.01, 4.34, and 3.65 mm day^{-1}, respectively (Fig. S7b; see Supplementary Material). The accumulated precipitation sheets also differed as a function of the phenological phase in each crop cycle (Fig. S7b; see Supplementary Material). In the cane plant cycle, phase IV showed the highest daily precipitation values (2.27 mm day^{-1}). However, in ratoon cycles 1 and 2, phase III showed the highest precipitation (2.88 and 2.01 mm day^{-1}, respectively) (Fig. S7b; see Supplementary Material). In addition, the monthly precipitation obtained in the experiment was 9.2% higher than the city's climatic average (31 years) for the cane plant cycle and 12.9% and 29.9% lower for ratoon cycles 1 and 2 (Fig. S7b; see Supplementary Material).

The average solar irradiance within the cane plant, ratoon 1, and ratoon 2 cycles equaled 17.5, 16.4, and 15.9 MJ m^{-2} day^{-1}, respectively, with average values within each phase between 15 and 19 MJ m^{-2} day^{-1} (Fig. S7c; see Supplementary Material).

Another agrometeorological variable evaluated was the thermal sum, which accumulated 2148.4 °C day (rate, 4.48 °C day^{-1}), 1616.4 °C day (rate, 5.05 °C day^{-1}), and 1621.1 °C day (rate, 5.07 °C day^{-1}) during the cane plant, ratoon 1, and ratoon 2 cycles, respectively (Fig. S7d; see Supplementary Material). The ratoon 2 cycle showed the highest thermal accumulation rates per phase (phase I, 0.62; II, 0.83; III, 2.35 °C day day^{-1}), except for phase IV, where the cane plant cycle showed the highest rate (2.56 °C day day^{-1}) (Fig. S7d; see Supplementary Material).

The average wind speed did not show significant differences between cycles or phases, averaging between 0.8 and 2.2 m s^{-1}.

The potential crop evapotranspiration (ETc) and actual evapotranspiration (ETa) showed cumulative (and daily) values of 1983.7 mm (3.6 mm day^{-1}) and 1138.8 mm (2.1 mm day^{-1}) (cane plant), 1064.2 mm (2.8 mm day^{-1}) and 723.5 mm (1.9 mm day^{-1}) (ratoon 1), and 1031.5 mm (2.9 mm day^{-1}) and 603.8 mm (1.7 mm day^{-1}) (ratoon 2), respectively. The accumulated water deficit (WD) was highest in the cane plant cycle (821.3 mm), followed by ratoon 2 (414.5 mm) and ratoon 1 (326 mm). The cycle length influenced the accumulated value. However, when determining the daily WD rates, the sequence between the highest and lowest values remained the same (cane plant, 1.5; ratoon 2, 1.2; ratoon 1, 0.86 mm day^{-1}) (Fig. S8a; see Supplementary Material). Regarding the water surplus (WS), the values were 853.4 (1.6 mm day^{-1}), 748.8 (2.0 mm day^{-1}), and 632.8 (1.8 mm day^{-1}) for cane plant, ratoon 1, and 2 cycles, respectively (Fig. S8a). Moreover, average ETa/ETc values were 0.56, 0.65, and 0.58 for cane plant, ratoon 1, and ratoon 2 cycles, respectively (Fig. S8a; see Supplementary Material).

Daily soil water storage (SWS) remained above the critical humidity ($SWS \geq RAW$) for much of the time (Fig. S8b; see Supplementary Material). The cane plant cycle was the exception which remained 53% of the time with soil humidity lower than critical. On the other hand, ratoon 1 (39%) and ratoon 2 (48%) cycles showed lower percentages (Fig. S9; see Supplementary Material). The phenological phase with the longest $SWS < RAW$ was phase IV for all cycles (Fig. S9; see Supplementary Material). It is worth noting that phase III remained about 20% of the time with humidity below critical for the cane plant and ratoon 2 cycles, but only 2% in the ratoon 1 cycle (Fig. S9; see Supplementary Material).

3.3 Yield estimates

The average real yields (Yr) for sugarcane obtained by the mill for the cane plant, ratoon 1, and ratoon 2 cycles were 118.5, 64.2, and 49.1 Mg ha^{-1}, respectively (Fig. 1A). Each crop cycle showed differences between estimated and real yields and a decreasing trend as a function of the number of harvests (Fig. 1A). Overall, the models generated overestimates regarding Yr (average, 22%), with the largest differences found by the Martins and Landell (ML) model in all crop cycles (cane plant, 35%; ratoon 1, 48%; ratoon 2, 34%) (Fig. 1A). The exceptions were detected using the Monteith model (M), which estimated values 31% lower than Yr in the cane plant cycle (Fig. 1A), and the Scarpari model (S) in ratoon cycles 1 and 2, where the differences were close to zero (Fig. 1A).

Regression equations were fitted to the estimated data as a function of Yr, obtaining high values of determination coefficients ($R^2 > 0.80$) (Fig. 1B). The angular coefficients < 1.0 confirmed the overestimates for most estimates, except for model M, which obtained an angular coefficient of 1.58 (Fig. 1B). The uncertainties of the models were determined using statistical indexes. Thus, the average value of Bias, root mean square error (RMSE), and mean absolute error (MAE) was 13.5 Mg ha^{-1} for the FAO-Agroecological Zone (AEZ) model and the FAO spectral (AEZs) (Fig. 1C). The

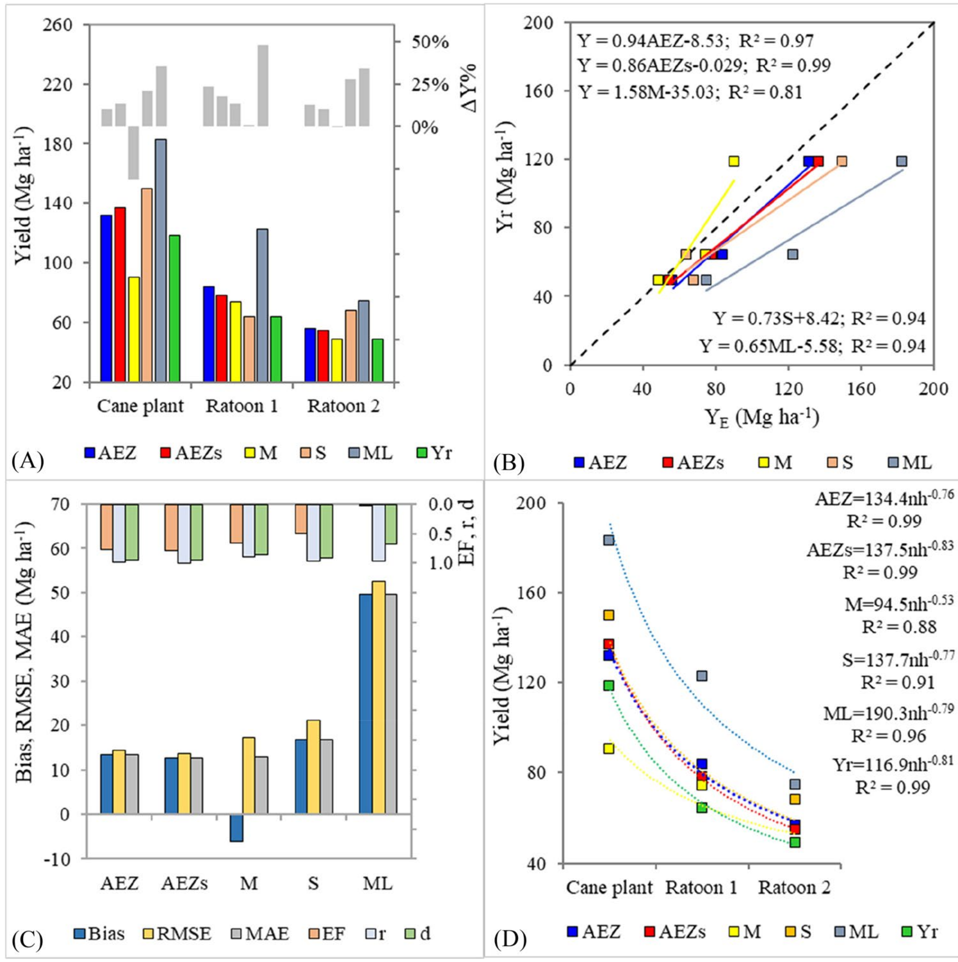


Fig. 1 Sugarcane yield estimated by the models FAO-standard (AEZ), AEZ modified with spectral data (AEZ_S), Monteith (M), Scarpari (S), Martins and Landell (ML), and real yield (Yr; sugarcane mill average), and their differences between the estimated and observed values (ΔY%) (**A**). Regression analysis between the yield estimated by the models and real yield (**B**). Statistical comparison indexes: Bias, root mean square error (RMSE), mean absolute error (MAE), modeling efficiency (EF), Pearson's correlation coefficient (*r*), and Wilmott's "*d*" coefficient (**C**). Yield decline coefficient (k_{dec}) as a function of the number of harvests (nh): cane plant; ratoon 1; ratoon 2 (**D**)

M model generated distinct Bias (−6.1 Mg ha^{-1}), RMSE (17.3 Mg ha^{-1}), and MAE (12.8 Mg ha^{-1}) results. Models S (18 Mg ha^{-1}) and ML (51 Mg ha^{-1}) obtained average values of Bias, RMSE, and MAE, positive and higher than the other models (Fig. 1C). The best model efficiency (EF), Pearson's correlation (*r*), and Wilmott's "*d*" were obtained by the AEZ (EF = 0.77; *r* = 0.98; *d* = 0.95) and AEZs (EF = 0.77; *r* = 0.98; *d* = 0.95) models. On the other hand, the ML model detected the worst indexes (EF ≈ 0.0; *r* = 0.96; *d* = 0.68) (Fig. 1C).

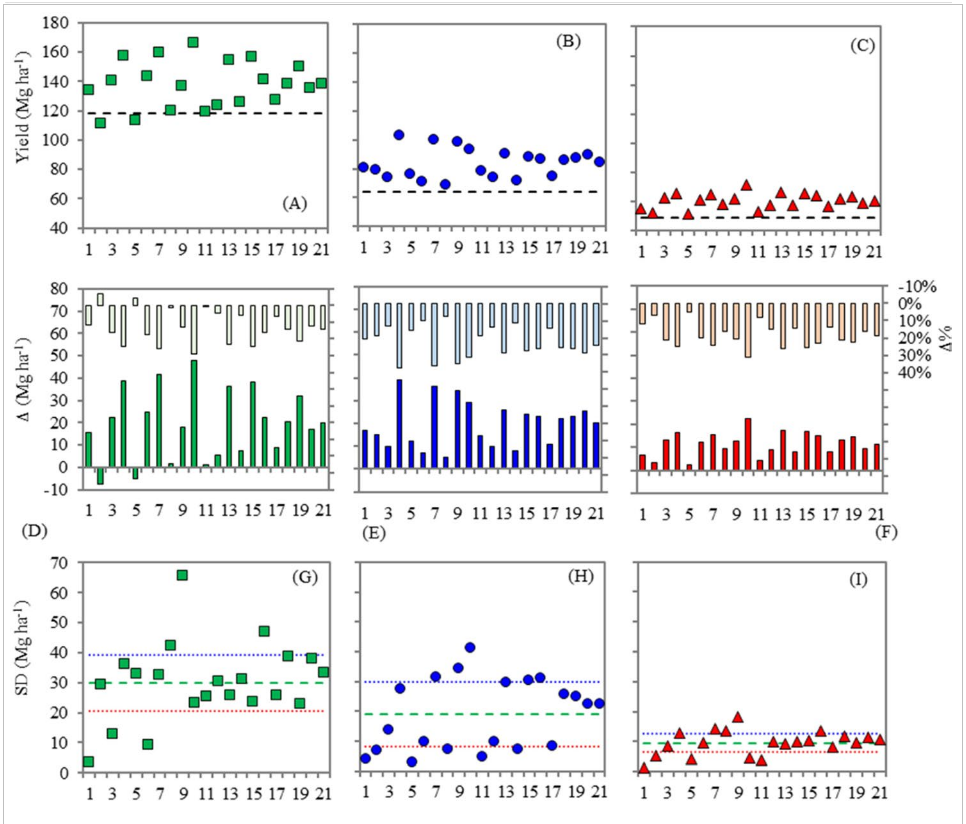
The exponential decline in yield as a function of the number of harvests recorded by the mill was also identified by the models, but with different decline coefficients (k_{dec}) (Fig. 1D). The k_{dec} found at Yr was equal to −0.81, whereas, for the models, these values ranged between −0.53 (M) and −0.83 (AEZs) (Fig. 1D).

3.4 Multi-model approach

The averages obtained by the models' combinations followed the yield decline between cane plant, ratoon 1, and ratoon 2 cycles (Fig. 2(A–C)). Most averages showed overestimations concerning the real yield (Yr), except for combinations 2 and 5 in the cane plant cycle (Fig. 2(A)).

The combinations that determined the smallest differences regarding Yr were 11 (Δ = 1.11 Mg ha^{-1}; Δ% = 1%), 8 (Δ = 5. 05 Mg ha^{-1}; Δ% = 7%), and 5 (Δ = 2.65 Mg ha^{-1}; Δ% = 5%), respectively, for cane plant, ratoon 1, and ratoon 2 cycles (Fig. 2(D–F)). On the other hand, the lowest standard deviations were obtained by combinations 1 (SD = 3.6; SD = 1.3) for cane plant and ratoon 2 cycles and 5 (SD = 2.78) for ratoon 1 (Fig. 2(G–I)).

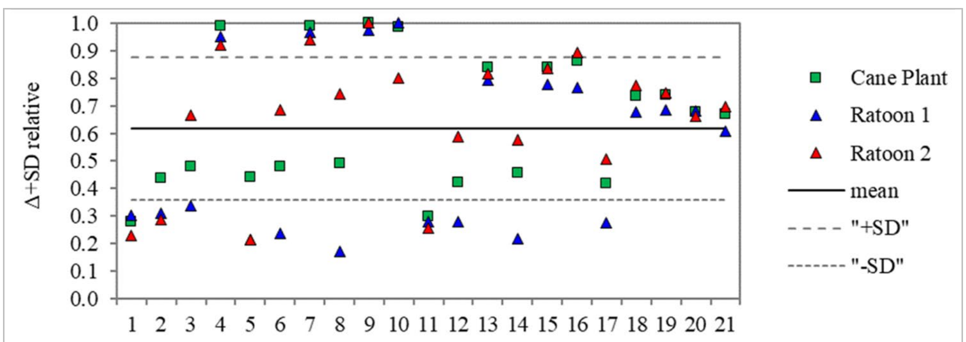
The sum of the relative values of the differences in yield (Δ) and standard deviation (SD) also generated relative values (Fig. 3). Thus, we could detect the model combinations that generated the lowest "relative Δ + SD" indexes, which averaged closer to the real yields, with less error (Fig. 3). Therefore, combinations 1 (AEZ + AEZs) and 11 (AEZ + AEZs + M) stood out. Regardless of the crop cycle, combinations 1 and 11 obtained "relative Δ + SD" values lower than the average, minus one standard deviation (− SD) (Fig. 3). These two combinations have the standard FAO models (AEZ), the agrometeorological-spectral models (AEZs), and the Monteith model (M), which also has spectral data as



Model combinations

1	AEZ	AEZs	8	M	S		15	AEZs	S	ML					
2	AEZ	M	9	M	ML		16	M	S	ML					
3	AEZ	S	10	S	ML		17	AEZ	AEZs	M	S				
4	AEZ	ML	11	AEZ	AEZs	M	18	AEZ	M	S	ML				
5	AEZs	M	12	AEZ	M	S	19	AEZ	AEZs	S	ML				
6	AEZs	S	13	AEZ	S	ML	20	AEZ	AEZs	M	ML				
7	AEZs	ML	14	AEZs	M	S	21	AEZ	AEZs	M	S	ML			

Fig. 2 Average sugarcane yield formed by 21 different combinations of FAO-standard (AEZ), AEZ modified with spectral data (AEZ_S), Monteith (M), Scarpari (S), and Martins and Landell (ML) models for the cane plant (A), ratoon 1 (B), and ratoon 2 cycles (C). Differences in yield (Δ, Mg ha^{-1}) and yield percentage (Δ%) between the 21 combinations of the models and the real yield (Yr) for the cane plant (D), ratoon 1 (E), and ratoon 2 cycles (F). Standard deviation (SD, Mg ha.$^{-1}$) for the cane-plant (G), ratoon 1 (H), and ratoon 2 cycles (I)



Model combinations

1	AEZ	AEZs	8	M	S		15	AEZs	S	ML		
2	AEZ	M	9	M	ML		16	M	S	ML		
3	AEZ	S	10	S	ML		17	AEZ	AEZs	M	S	
4	AEZ	ML	11	AEZ	AEZs	M	18	AEZ	M	S	ML	
5	AEZs	M	12	AEZ	M	S	19	AEZ	AEZs	S	ML	
6	AEZs	S	13	AEZ	S	ML	20	AEZ	AEZs	M	ML	
7	AEZs	ML	14	AEZs	M	S	21	AEZ	AEZs	M	S	ML

Fig. 3 Sum of the relative values of the yield difference (estimated and actual) and the standard deviations (Δ + SD relative) of each of the 21 combinations formed by the FAO-standard (AEZ), AEZ spectral (AEZS), Monteith (M), Scarpari (S), and Martins and Landell (ML) for the cane plant, ratoon 1, and ratoon 2 cycles. The mean (mean) and standard deviations (+ SD and − SD) were also determined by "Δ + SD relative"

input. The worst results, regardless of the crop cycle, were achieved by combinations 4 (AEZ + ML), 7 (AEZs + ML), and 9 (M + ML), which have the addition of the Martins and Landell (ML) model as a common feature (Fig. 3).

4 Discussion

4.1 Plant growth, agrometeorological data, and limited water

Identifying a stalk growth pattern is of utmost importance since there is a strong positive correlation between stalks and sugarcane yield (Carlin et al. 2008). Authors have been detecting in Brazil and worldwide a sigmoidal behavior of sugarcane growth, passing three phases: the first slow, a second with accelerated growth, and ending with a stabilization (Inman-Bamber 1994, 2004; Oliveira et al. 2010; Almeida et al. 2008; Gava et al. 2011; Segato and Carvalho 2018; Casaroli et al. 2023; Caetano et al. 2023). Thus, crop models that consider biometric variables can be applied when this behavior is identified.

In order to reach a potential yield (ethanal and sugar), the sugarcane crop needs a growing environment with a warm (average temperature between 25 and 35 °C) and humid (precipitation between 1500 and 2500 mm) climate with high solar radiation intensity (between 18 and 35 MJ m^{-2} day^{-1}) in the crop growth phase, followed by a water restriction (> 120–130 mm) or a thermal reduction (< 21 °C), to stimulate sucrose storage in the stalks (Camargo and Ortolani 1964; Câmara and Oliveira 1993; Inman-Bamber 1994, 2004; Scarpari and Beauclair 2004; Inman-Bamber and Smith 2005; Monteiro 2009; Cardozo and Sentelhas 2013).

In this study, the mean air temperature was lower than that suggested in the literature as the optimal range (Ta = 23.9 °C; Fig. S7a; see Supplementary Material) but above the lower basal temperature (Tb = 16 °C). Cumulative precipitation met crop requirements in the cane plant cycle (≥ 1500 mm) but was lower in the other cycles (Fig. S7b; see Supplementary Material). On the other hand, solar radiation obtained average values lower than recommended (between 15.9 and 17.8 MJ m^{-2} day^{-1}; Fig. S7c; see Supplementary Material).

For different sugarcane varieties, water deficit (TAW ≤ 20%), when applied in the early stages, can reduce transpiration by 67% and photosynthesis by 78% (Gonçalves et al. 2010). When it occurs at the establishment and/or rapid vegetative growth stages, there is a reduction in phytomass (35%), sucrose (25%) (Inman-Bamber and Smith 2005; Machado et al. 2009), elongation (60%) and diameter (55–75%) of stalks (Ecco et al. 2014), and leaf area index (50%) (Santos 2018).

Paixão et al. (2020) divided the state of Goiás, Brazil, into five groups as a function of total available water capacity (TAW), obtaining a range from 0–50 mm to 150–250 mm, where the highest laminas were associated with the highest yields. The municipality of Santo Antônio de Goiás (this study's site) was classified within the higher TAW range but is not within the group with the highest yields. This same study showed that the municipality obtained one of the lowest precipitations and the highest air temperatures, possibly generating a greater water deficit, which would explain the lower yields (46.4 ± 10.8 Mg ha^{-1}), being below the Brazilian average (Yr = 74.7 Mg ha^{-1}) (FAO 2022).

In this study, the maximum TAW was 190.8 mm, obtained as a function of the root system (Fig. S8b; see Supplementary Material). This water availability generated an average ETa/ETc ratio of 0.60 for cane plant, ratoon 1, and ratoon 2 cycles (Fig. S8a; see Supplementary Material), achieving average yield values of 118, 64, and 49 Mg ha^{-1}, respectively (Fig. 1). This decline in productivity as a function of successive cuttings is commonly found in the literature (Bernardes et al. 2008; Casaroli et al. 2019).

4.2 Actual yield and decline factor

Real yield data (Yr, Mg ha^{-1}) of sugarcane from 256 municipalities in the state of Goiás, Brazil, showed an average variation of 32.4 ± 69.4 Mg ha^{-1}. The municipality of Santo Antônio de Goiás obtained a Yr of 46.4 ± 10.8 Mg ha^{-1} (Paixão et al. 2020), being lower than the average of the three cycles (Yr = 77.3 ± 27.5 Mg ha^{-1}) found in this work (Fig. 1A), although within the standard deviation.

Studies with different Brazilian varieties have not shown significant differences in yield during the cane plant cycle (range, 76 ± 102 Mg ha^{-1}). However, these values were significantly higher than those obtained in the ratoon cycle (2nd cut) (range, 65 ± 95 Mg ha^{-1}). This yield drop was attributed to the water deficit, in which 33% of the deficit (181 mm) occurred up to 80 days before the harvest of the first crop, damaging the ratoon sprouting. This situation was aggravated by the rest of the deficit (363 mm) that occurred in the initial 130 days of crop development (Abreu et al. 2013).

Yield shortfalls between cane plant and ratoon cycles were also obtained in this study (Fig. 1), where phase IV of the cane plant cycle (≈ 200 DAP) accumulated a water deficit of 324.1 mm, representing 39% of the total. For ratoon cycles 1 and 2, the accumulated deficit in this phase represented 54 and 48% of the total. It is also worth noting that the sprouting phase (I) in the ratoon cycles accumulated an average deficit of 35 mm, or 10% of the total (Fig. S8 and S9; see Supplementary Material).

Another important point to be addressed is yield shortfalls due to successive sugarcane harvests (Fig. 1D). Under Central Brazilian conditions, there is a variation in yield between 60 and 120 Mg ha^{-1}, for up to 5 years, with the highest value recorded in the first year of harvest (Thiago and Vieira 2002; Dias and Sentelhas 2017). Despite the lack of a physiological explanation, empirical evidence shows a decline in yield with the number of harvests in commercial crops (Bernardes et al. 2008; McGlinchey and Dell 2010), which are attributed to substandard management practices such as high pest, disease, and weed pressure, decreased soil fertility, soil compaction, and physical damage caused to the crop by mechanical harvesting (Jackson 1992; Dinardo-Miranda et al. 2002; Christoffoleti et al. 2006; Srivastava and Chauhan 2006; Vitti et al. 2007; Marin et al. 2019; Flores et al. 2020).

For Brazilian cultivars, exponential yield decline seems to be a good estimate (Bernardes et al. 2008; Dias and Sentelhas 2017). This study observed this trend but with larger decline coefficients (k_{dec}). While Dias and Sentelhas (2017) obtained $k_{dec}=0.21$ for the municipality of Bom Jesus de Goiás (Goiás State, Brazil), our k_{dec} was 0.81 (Fig. 1D). Other authors have described that the values of k_{dec} ranged from 0.10, which represents good crop management, to 0.40, reflecting inadequate management practices (Bernardes et al. 2008). Similarly, Rossi et al. (2012) obtained k_{dec} values between 0.37 and 0.51, again indicating a low level of crop management, which may be associated with poor soils, soil compaction, and suboptimal pest, disease, and weed controls.

4.3 Crop models

Crop productivity can be estimated by biometric parameters, considering as sugarcane productivity components the diameter, the length of the stalks, the number of stalks per area, associated with tillering capacity, and the stalk density (Landell and Silva 1995; Ferreira et al. 2007; Silva et al. 2009). All these are genetic traits yet subject to environmental influence (Skinner 1965). Cuadra et al. (2012) developed and validated a new process-based model for estimating sugarcane yield. The simulated annual average sugarcane yields over 31 years for the state of Louisiana (US) had a low relative bias (2.67%), but exhibited a lower interannual variability than the observed yields.

The FAO-Agroecological Zone (AEZ) (Doorenbos and Kassam 1979) model has a simple structure regarding simulated processes and parameters. Still, it has generated satisfactory results when properly adapted to regions of interest for agrometeorological studies related to sugarcane in Brazil (Monteiro and Sentelhas 2014, 2017; Scarpare et al. 2016; Dias and Sentelhas 2017, 2018; Paixão et al. 2021). Furthermore, when the AEZ model is associated with a yield decline factor as a function of the number of harvests, it improves sugarcane yield estimates (Dias and Sentelhas 2017).

When applying the AEZ model, different potential yields (Yp) for the cane plant and ratoon cycles are found in the literature (i.e., cane plant, 290; ratoon 1, 160; ratoon 2, 75 Mg ha^{-1}), which are justified by the different number of days in the cycle, where greater time in the field would provide greater dry matter accumulation (Caetano and Casaroli 2017; Caetano et al. 2021). In this study, the Yp values were equal to 379, 164, and 152 Mg ha^{-1}, respectively, for the cane plant, ratoon 1, and ratoon 2 cycles. Simulations of Yp for sugarcane, with yields weighted as a function of areas cultivated with cane plant (20%) and ratoon (80%) (259 sites in Brazil), determined ranges of 68.5–232.7 Mg ha^{-1}, which resulted in an average total "yield gap" of 133.2 Mg ha^{-1}, with water deficit accounting for 75.6% of total losses, while crop management accounts for 24.4% (Monteiro and Sentelhas 2014). Thus, the authors suggest using drought-tolerant cultivars, irrigation, and deep soil preparation to mitigate risks while improving productivity.

In the state of Goiás, Caetano and Casaroli (2017) detected yield shortfalls both due to water deficit (cane plant, 128. 9; ratoon 1, 91.84; ratoon 2, 82. 5 Mg ha^{-1}), as due to deficit and management (cane plant, 112. 8; ratoon 1, 49.6; ratoon 2, 51.9 Mg ha^{-1}), which generated statistical indexes with larger errors than those found in this study (RMSE = 32.2 Mg ha^{-1}, MAE = 30.2 Mg ha^{-1}, and $d=0.92$) (Fig. 1B).

Paixão et al. (2021) simulated different planting dates of sugarcane (AEZ-FAO model; 12-month cycle) and obtained for the central region of the state of Goiás (this study's site) an average value of achievable yield (Ya-limiting water) equal to 104 ± 44 Mg ha^{-1}. It is worth noting that the best planting window was from May 01 to Aug 01 (119 Mg ha^{-1}), having as a third option the planting on Apr 16 (111 Mg ha^{-1}), which is close to this study's planting date (Apr 01).

In order to improve the sampling of large areas, yield estimation studies from the use of agrometeorological data associated with remote sensing (RS) imagery and geographic information systems (GIS) make it feasible to generate state and national level forecasts (Rudorff and Batista 1990; Hartkamp et al. 1999; Mo et al. 2005; Rizzi and Rudorff 2007; Mussi et al. 2020; Rezaei et al. 2021). Thus, in research in Brazil, the agrometeorological-spectral model (AEZs) underestimated the average sugarcane yield by 14.6% (13.4 Mg ha^{-1}) for the first crop but overestimated it by 1.8% (1.4 Mg ha^{-1}) for the second crop (Yr of 91.9 and 79.2 Mg ha^{-1} for the first and second harvests, respectively). Furthermore, this model managed to explain 31% of the variability (MSE = 20.9 Mg ha^{-1}; $d=0.87$) of the yield observed in the first crop and 25% in the second crop (MSE = 19.2 Mg ha^{-1}; $d=0.62$), with the authors recommending this model (Picoli et al. 2009). In this study, the values estimated by AEZ_S overestimated the yields in all crop cycles (Fig. 1A). These differences may be due to the resolution for collecting spectral data (Picoli et al. 2009) or to the spatial resolution of the model proposed by Doorenbos and Kassam (1979) and are not adequate to estimate the agricultural yield of sugarcane at the plot scale (up to 40 ha), corroborating Teramoto (2003). Some authors (Pereira et al. 2016) report the importance of performing atmospheric correction for determining the leaf area index (LAI) from the normalized difference vegetation index (NDVI) and thus obtaining better results in these estimates (R^2 = 0. 84; d = 0.95; MAE = 0.44; RMSE = 0.55), which was performed in this study.

Working with the model proposed by Monteith (1972) coupled with the SEBAL (surface energy balance algorithm for land) algorithm (Bastiaanssen and Ali 2003), which was developed by Bastiaanssen et al. (1998a, 1998b), Andrade et al. (2014) estimated sugarcane yields in different cropping areas and harvests. Thus, the best results showed statistical index values equal to d = 0.70, MAE = 5.96 Mg ha^{-1}, and RMSE = 7.31 Mg ha^{-1}, with some plots showing maximum absolute differences of 2 Mg ha^{-1} regarding Yr. On the other hand, the largest differences were on the order of 14 Mg ha^{-1}. The authors report that the errors corroborate those found in the literature and justify these differences by the possible attack of pests, diseases, and cultural treatments in the different crop areas (Campos et al. 2010) and the image's spatial resolution (Picoli et al. 2009). In this study, the "d," RMSE, and MAE values were higher (0.86, 17.3, and 12.8 Mg ha^{-1}, respectively) (Fig. 1C). In contrast, the average absolute difference showed average values (ΔY = 6 Mg ha^{-1}) (Fig. 1A).

Some studies point to good results from simple models that express yield as a function of agrometeorological variables (precipitation, evapotranspiration, air temperature) (Ometto 1974; Culverwell 1984; Rojas 1991). Other studies point to poor reliability, for example, of the model proposed by Scarpari (Scarpari 2002), or also describe overestimation regarding experimental values (cane plant, 53%; ratoon 1, 23%; ratoon 2, 19%) (Caetano and Casaroli 2017), as observed in this study (> 20%), except for the ratoon 1 cycle, where the difference was ≈0% (Fig. 1A).

The biometric model proposed by Martins and Landell (1995) is widely used in yield estimates in experiments in Brazilian productive areas (i.e., Carlin et al. 2008; Oliveira et al. 2007, 2010, 2011). However, reports show that this model can promote differences of up to 20% regarding the real yield (experimentally obtained) (Araújo et al. 2019), which were also observed in this study (Fig. 1A).

Recent studies have shown that using a set of crop simulation models in a multi-model approach reduced the uncertainties associated with the simulations of each model individually, as observed for several crops, including sugarcane (Marin et al. 2015; Dias and Sentelhas 2017). Thus, when using a set of models (AEZ-FAO, DSSAT/CANEGRO, and the APSIM-Cane) applied in three municipalities in the state of Goiás, Brazil, the potential (Yp), achievable (Ya), and real (Yr) sugarcane yield estimates for a simulation with a 12-month cycle were 198.1, 115.1, and 60.6 Mg ha^{-1}, respectively (Dias and Sentelhas 2018).

Other authors have worked with the BioCro model, which simulates hourly plant growth based on underlying conditions from biophysical and biochemical mechanisms, using site-specific soil, properties, and hourly meteorological records. Furthermore, it is important to highlight that the model includes processes that respond interactively to increases in CO_2, temperature, and incidence of droughts. BioCro's performance was evaluated in relation to yield data measured independently in several regions of Brazil, obtaining satisfactory results (error = 29 tons ha^{-1}; concordance correlation coefficient = 0.90) (Jaiswal et al. 2017).

5 Conclusions

The biometric variables showed similar behaviors among cycles and the phenological phases of each cycle, fitting Sigmoid, Gaussian, exponential, and log-normal models, with a high level of adjustment (R^2 > 0.90). Both the behavior and the maximum and average biometric values were consistent with literature results, enabling their use in models.

When growth rates started to decrease, there were no inappropriate agrometeorological variables and/or soil humidity that could promote such behavior.

The FAO-agroecological Zone, agrometeorological-spectral, Monteith, and Scarpari models can be recommended for individual sugarcane yield estimates with a lower degree of uncertainty. Furthermore, all models detected a decline in yield as a function of the number of harvests.

The multi-model approach decreased the differences between estimated and real yields, where the combinations between the "AEZ + AEZs" and "AEZ + AEZs + M" models stood out.

6 Author contribuition

All authors contributed to the study conception and design. Material preparation, data collection, and first analysis were performed by Dayanna Teodoro Quirino and Grazieli Rodigheri. The analysis of results and discussion of the manuscript was performed by Derblai Casaroli, Ieda Del'Arco Sanches, Dayanna Teodoro Quirino, and Grazieli Rodigheri. The first draft of the manuscript was written by Derblai Casaroli. The revised version was performed by Derblai Casaroli, Adão Wagner Pêgo Evangelista, José Alves Júnior, Rilner Alves Flores, Marcio Mesquita, Rafael Battisti, and Frank Freire Capuchinho, and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Author contributions All authors contributed to the study conception and design. Material preparation, data collection and first analysis were performed by D.T.Q. and G.R. The analysis of results, discussion of the manuscript was performed by D.C., I.D.S., D.T.Q. and G.R.. The first draft of the manuscript was written by D.C. The revised version was performed by D.C., A.W.P.E., J.A.J., R.A.F., M.M., R.B., F.F.C.; and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Code availability Not applicable.

Declarations

Ethics approval Not applicable.

Consent to participate All the authors are aware and agree with this submission.

Consent for publication All the authors agree with the publication of the papel in Theoretical and Applied Climatology.

Competing interests The authors declare no competing interests.

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