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On-farm sugarcane water productivity influenced by environmental and management practices in Brazil

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ABSTRACT: Quantifying the impact of driving factors on crop water productivity (WP) is essential for efficient agricultural water use. To date, few studies have investigated the influence of management and environmental factors on sugarcane WP at the mill scale. This study aimed to assess the contributions of management practice factors, weather variables, and soil management zones (SMZs) on on-farm sugarcane WP in a single mill in the southern region of Brazil. An extensive on-farm database of commercial sugarcane field plots was used with a weather database to estimate evapotranspiration and water-limited potential yield (Yw). This was achieved by employing a crop sugarcane model to calculate actual water productivity (WPa) and attainable water productivity (WPw). The results demonstrated an inverse relationship between management practices and WPa, while harvest date and vinasse positively impacted on WPa. The Yw, actual yield (Ya), actual evapotranspiration (ETa) or crop evapotranspiration (ETc), and WPa varied according to the SMZ. The lowest WPa values were observed in the worst soils. The analysis revealed that weather variables collectively accounted for 46.2 % of WPa variability, management practice factors accounted for 40.5 %, and SMZs contributed 13.3 % of WPa variability. Despite weather variables being the primary source of WPa variability, management practice factors still played a key role in WPa variability.

Keywords: crop model, on-farm data, sugar-energy industry, sugar mill

Introduction

Sugarcane accounts for nearly 75 % of the world's sugar production for human consumption (Souza et al., 2008). Brazil is responsible for roughly 40 % of sugarcane globally. The country accounts for 50 % of global sugar exports and is the world's second largest ethanol producer.

Sugarcane irrigation in Brazil is still a recent practice, accounting for approximately 10 % of the crop area; nevertheless, the expansion of sugarcane plantations into warmer and drier regions could intensify competition among water-consuming sectors in Brazil. This is particularly relevant when considering the implications within the broader context of global change scenarios (Marin et al., 2020; Oliveira et al., 2018; Silva et al., 2013). The potential irrigated area in Brazil is estimated to be 29.3 Mha (FAO, 2017), which would aggravate the current scenario if such an area were cultivated under irrigation. Reduced water availability may intensify the stress in an already vulnerable context, with water scarcity being identified as a significant factor limiting sugarcane production in Brazil (Scarpare et al., 2016a).

The term "water productivity" (WP) is defined as the ratio of crop yield per unit of water used. Water productivity has been recognized as a comprehensive indicator of water use efficiency for the purpose of comparing crops, regions, and/or farming systems (Farias-Ramírez et al., 2024) and WP has been a topic of extensive discussion in the literature worldwide, particularly in the context of the challenge of increasing biomass production while using less water. However, improvements in WP in rainfed farming systems could potentially impact the national water situation by redirecting water runoff to evapotranspiration and enhancing WP in national-scale bioenergy production (Berndes, 2002; Hellegers et al., 2009).

In Brazil, the ethanol industry plays an important economic role, and its impact on water resources at a national scale has been a subject of discussion (Walter et al., 2014). Several studies have been conducted globally to examine the impact of sugarcane WP (Carr and Knox, 2011; Lata, 2019; Meyer, 1977); however, no study has yet investigated the impact of management practices on sugarcane WP at the mill scale. This represents a significant gap in the existing literature. Therefore, this study aimed to investigate the effect of weather variables and the most commonly utilized management practices on on-farm sugarcane WP. To this end, we analyzed an extensive database from one mill located in the main producing region of Brazil (a total of 9,152 block-year observations).

Materials and Methods

Study site

Data on sugarcane yield and management practices were collected for the same group of sugarcane field plots from a mill in São Paulo State, Brazil over a five-year period (2013-2017) (Table 1). In the study site, sugarcane is typically planted or begins to regrow during the months of Oct through May. It can be harvested at any point between 12 and 18 months after sprouting, with the precise harvest time dependent upon the demand for sugar by mills. It is cultivated under rainfed conditions. The climate is tropical, and the weather variables were retrieved from six weather stations, including solar radiation, maximum temperature, minimum temperature, and total rainfall (Table 2) (Alvares et al., 2013). For each block, the meteorological data of the nearest weather station were assigned based on the mill shapefile map.

Rainfall events are concentrated from Sept to Mar, with a northeast decreasing trend in temperature, with maximum values recorded during Jan and Feb. The main growth phase of sugarcane is compared to annual patterns in weather variables (Figure 1). The highest biomass accumulation rates are achieved in the most rainy and warmest periods of the year, whereas mild water stress and cooler temperatures reduce crop vegetative growth and favor sucrose storage in the stalks (i.e., harvest periods, as illustrated in Figure 1).

Table 1 – Description of variables collected from sugarcane plots.

Variables (and acronyms)	Unit/Class
Block location	Latitude, longitude
Block area	ha
Ya	Mg ha^{-1}
SMZ	Classes I ('good') to V ('poor')
Crop cycle	DAP
Harvest number[a]	H1 to H5
Planting date	Year and DOY
Harvest date	Year and DOY
Growth regulator	L ha^{-1}
Vinasse	m^3 ha^{-1}
Filter cake	Mg ha^{-1}
Lime	Mg ha^{-1}
Gypsum	Mg ha^{-1}

[a]Harvest number in a given block. The class H1 corresponds to first ratoon and subsequent harvests [H2 to H5] correspond to the successive ratoon crops. Plots with number of harvests > 5 were not included. SMZ = soil management zone; Ya = actual yield in terms of stalk fresh mass; DAP = days after planting; DOY = day of the year.

In accordance with the United States Department of Agriculture (USDA) soil taxonomy, the predominant soil classes identified within the sugar mill area are the Rhodic Hapludox, which exhibit a degree of variability in texture, predominantly a sandy-clay (Dalmolin et al., 2004; USDA, 1999).

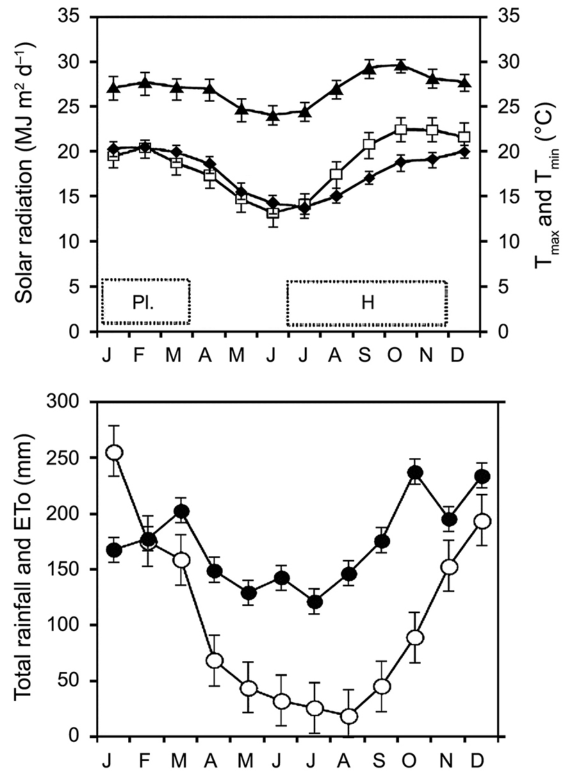

Figure 1 – Monthly means for daily incident solar radiation (□), maximum and minimum temperature (T_{max} [▲] and T_{min} [♦], respectively), total rainfall (○), and total reference evapotranspiration (ETo [●]) based on long-term (2001-2019) weather records collected from six meteorological stations located within the study site. Horizontal bars indicate the standard error of the mean. Typical planting (Pl.) and harvest (H) windows are also shown in the upper panel.

Table 2 – Average (± standard error) daily solar radiation, maximum (T_{max}) and minimum (T_{min}) temperatures, total rainfall, and total grass-reference evapotranspiration (ETo) within the study area in Southeast Brazil during the 2013-2019 seasons. Long-term (2001-2019) means are also shown.

Crop season	Solar radiation	T_{max}	T_{min}	Total rainfall	ETo*
	MJ m^{-2} d^{-1}	------------------------ °C	------------------------	------------------------ mm	------------------------
2013	18.2 ± 0.4	26.4 ± 0.2	17.4 ± 0.3	1,154 ± 8	142 ± 4
2014	19.7 ± 0.5	28.2 ± 0.3	18.3 ± 0.3	815 ± 7	153 ± 4
2015	18.4 ± 0.4	27.4 ± 0.3	18.6 ± 0.3	1,432 ± 11	143 ± 4
2016	18.6 ± 0.4	27.1 ± 0.2	17.6 ± 0.3	1,431 ± 11	145 ± 4
2017	18.7 ± 0.4	27.4 ± 0.3	18.1 ± 0.3	1,356 ± 12	146 ± 4
2018	18.1 ± 0.3	27.9 ± 0.1	18.4 ± 0.2	1,215 ± 9	141 ± 3
2019	19.3 ± 0.5	27.3 ± 0.3	19.3 ± 0.3	1,195 ± 10	152 ± 5
19-year mean	18.6 ± 0.1	27.0 ± 0.1	17.8 ± 0.1	1,255± 2	146 ± 1

*ETo was estimated using the Priestley-Taylor method.

On-farm database description

The variables pertaining to each block are described in Table 1, including the block location, the block size, the actual yield (Ya), the soil management zone (SMZ), the number of harvests (i.e., the number of consecutive harvests in each block), the crop cycle, the planting date, the harvest date, the quantity of growth regulator, the volume of vinasse per hectare, as well as the quantity of filter cake, lime, and gypsum per hectare (Table 1).

The data were subjected to a screening process to remove erroneous and incomplete data entries. For each block-year, entries exceeding the observed mean by more than 1.5 standard deviations were excluded. Additionally, plots with a number of harvests greater than five ratoons were removed, as these are highly unusual occurrences in sugarcane plantations. Following the quality control procedure, the database comprised 8,656 block-year entries.

The SMZ is a generic classification method utilized by Brazilian sugar mills to differentiate soil types in terms of suitability for sugarcane production. This classification system encompasses a total of five SMZs, ranging from favorable (SMZ I) to poor (SMZ V) soils for sugarcane cultivation. The SMZs are defined according to three criteria: soil water holding capacity, drainage rate, and chemical attributes (pH, cation exchange capacity, nutrient availability) (Prado, 2005). The SMZ classification method is used consistently across regions, mills, and producers to inform decisions on variety, planting, harvest, and other management practices at the block level.

Crop model setup and simulations

The DSSAT/CANEGRO (DC) model was employed to simulate the potential yield of sugarcane under water-limited (Yw, Mg ha^{-1}) and crop evapotranspiration (ETc, mm) throughout the crop cycle (Jones et al., 2003; Singels et al., 2008; Hoogenboom et al., 2019). The Yw of an adapted crop cultivar is the yield that can be achieved when the crop is grown with non-limiting nutrients and effectively controlled biotic stress. However, the Yw is limited by the amount and distribution of rainfall during the crop growing season. The physiological explanation of sugarcane's growth and development processes, including phenology, canopy development, tillering, root growth, biomass accumulation and organ partitioning, water stress, and lodging, form the basis of this model (Singels et al., 2008). The crop model simulates water consumption, as described in Marin and Jones (2014), using an adaptation of the Priestley and Taylor (1972) technique and calculates canopy development, radiation interception, potential soil evaporation, and potential plant transpiration. The actual evapotranspiration (ETa) was calculated by adding the actual evaporation to the actual transpiration. The actual evaporation was simulated by scaling down the potential soil evaporation by a reduction factor calculated using the relative water content (RWC), defined as the ratio between the current volumetric water content and the water content at saturation (Van Keulen and Seligman, 1987). The actual transpiration was simulated based on the root water uptake, which considers the soil moisture and root length density. The actual evaporation was simulated using an adaptation described by Ritchie (1998).

The calibration provided by Marin et al. (2015) was employed to minimize the root mean square error (RMSE) for stalk fresh mass and leaf area index using field data for the cultivar RB867515, which is cultivated on approximately one-third of the sugarcane area in Brazil (Marin et al., 2014). The experimental data utilized for model calibration were obtained from seven trials conducted across Brazil over several years in various climates and soil types representative of the main sugarcane-producing regions. These trials were conducted under good management practices. Consequently, the yields observed in these studies were close to Yw for each site, and indicative of Yw across years and the major Brazilian sugarcane-producing regions. Following calibration, the DC model accurately replicated the temporal growth dynamics in stalk fresh mass and leaf area index. Furthermore, the harvest-measured stalk fresh mass (ranging from 77 to 152 Mg ha^{-1}) exhibited a reasonable degree of agreement with the simulated values (RMSE = 16.5 Mg ha^{-1}).

Our analysis aimed to estimate the on-farm actual water productivity (WPa) and attainable water productivity (WPw) for rainfed sugarcane. These estimates are expressed as:

$$WPa = \frac{Ya}{ETa} \tag{1}$$

$$WPw = \frac{Yw}{ETc} \tag{2}$$

where WPa with dimensions of Mg ha^{-1} mm^{-1} is defined as the ratio of Ya (Mg ha^{-1}) to the depth of water consumed by the crop (ETa [mm]), and WPw is the ratio of Yw (Mg ha^{-1}) to ETc (mm). ETa is the actual evapotranspiration, and refers to water loss either by soil evaporation and crop transpiration during the crop cycle. ETc is the crop evapotranspiration under standard conditions, with no limitations on crop growth (Allen et al., 1998).

For each block, Yw was simulated for each growing season, considering the number of harvests, the planting and harvesting dates, and the SMZ provided by the mill.

Identification of sources of yield variability

A regression analysis was employed to examine the correlation between WP and the various management factors, including filter cake (Mg ha^{-1}), lime (Mg ha^{-1}), gypsum (Mg ha^{-1}), vinasse (m^{3} ha^{-1}), growth regulator (L ha^{-1}), and crop cycle. To determine the extent to which each factor influences WP, we employed the slope and intercept of the linear equation, and Pearson's correlation coefficient (Snedecor and Cochran, 1982). For the factors significantly correlated with WP based on the regression analysis ($p < 0.05$), further investigation was conducted using the Tukey's test to compare means. To represent the spatial variability in the mill, maps with the averaged WP were produced using ESRI ArcMap 10.5 software, and frequency distributions were used to assess variation in WP.

The plots were grouped into four quadrants, and a threshold of mean values was employed to identify plots related to WPa and management practice factors: (I) WPa < 84.7 Mg ha^{-1} mm^{-1}, management factor < mean; (II) WPa ≥ 84.7 Mg ha^{-1} mm^{-1}, management factor < mean; (III) WPa ≥ 84.7 Mg ha^{-1} mm^{-1}, management factor ≥ mean; and (IV) WPa < 84.7 Mg ha^{-1} mm^{-1}, management factor ≥ mean.

In order to understand sources of variation for WP across block years, we calculated the contribution rates (E) of driving factors (rainfall, maximum and minimum temperature, incident solar radiation, SMZ, planting date, harvest date, crop cycle, vinasse) on WPa by the partial least squares method (PLS) (Mevik and Wehrens, 2007). This method was selected to avoid the issue of multicollinearity among the driving factors. PLS is a statistical method used to model causal paths between sets of variables, referred to as latent variables (LVs) or constructs. In PLS, the LVs and paths constitute the inner model, also known as the structural model, while the measured variables (MVs) form the outer or external model. In the inner model, the connections between LVs are quantified using path coefficients (β), while the links between LVs and MVs in the outer model are quantified using weights. The regression coefficients that connect the latent variables to the original X and Y variables are represented in the parameters β. This approach allows for the analysis of complex relationships between variables and the construction of predictive models.

To measure E, which refers to the effect of changes in driving factors on WPa variation, we considered the β parameters estimated by the PLS package conducted in RStudio. These were obtained for the entire period (2013-2017) and five sub-periods, that is, 2013, 2014, 2015, 2016, and 2017. The sum of E for all analyzed driving factors for each analyzed period is 100 %.

Results

The crop cycle exhibited an inverse relationship with WPa, whereas vinasse demonstrated a positive impact on WPa ($p < 0.05$) (Table 3). Notably, the results indicated that the application of filter cake ($p = 0.45$), lime ($p = 0.95$), gypsum ($p = 0.86$), and growth regulator ($p = 0.49$) did not exhibit a significant impact on WPa. This suggests that shorter crop cycles may enhance WPa, with vinasse demonstrating relatively higher responsiveness than other significant factors. The findings indicate that each m^3 ha^{-1} applied vinasse can potentially elevate WPa by 0.23 Mg ha^{-1} mm^{-1}.

Table 3 – Coefficients of linear regression (intercept and slope) and correlation (r) between actual water productivity (WPa) and the management factors.

Management factor	WPa (Mg ha^{-1} mm^{-1})		
	Intercept	Slope	r
Filter cake (Mg ha^{-1})	-	–0.15^{ns}	-
Lime (Mg ha^{-1})	-	0.04^{ns}	-
Gypsum (Mg ha^{-1})	-	0.09^{ns}	-
Vinasse (m^3 ha^{-1})	62.42*	0.23*	0.145
Growth regulator (L ha^{-1})	-	0.31^{ns}	-
Crop cycle (DAP)	90.52*	–0.01*	–0.029

*Significance at $p < 0.05$; ns = not significant (all values with ns were also tested for $\alpha < 0.01$, with no significance). Quadratic effects were not significant. Intercept and r values were not shown for those factors in which slope was not significant. DAP = days after planting.

With regard to vinasse, the majority of plots were situated within quadrant III (30 % of the total number of plots) (assuming an average value of 93.0 m^3 ha^{-1}) and accounted for 24 % of the total number of plots in the minority, falling within quadrant II (Figure 2A). The crop cycle (with an average duration of 365 DAP) exhibited the most plots in quadrant III, with 29 % of the total plots, while 22 % were situated in the minority in quadrant I (Figure 2B).

Yw, Ya, and ET (ETa or ETc) exhibited variability according to the SMZ, with the lowest Yw, Ya, and ET observed in the most severely degraded soils (Figure 3). The plots situated in SMZ I exhibited elevated values for Yw, Ya, and ETa, which were statistically equivalent to those observed in SMZ II. The plots within SMZ I demonstrated 890 mm, 78.8 Mg ha^{-1}, and 116.7 Mg ha^{-1} for ET, Ya, and Yw, respectively (Figure 3). SMZ III was statistically equivalent to SMZ IV, and both were statistically distinct from SMZ I and SMZ II. The ETc for SMZ III was 847 mm, with 68.3 and 96.4 Mg ha^{-1}, respectively, for Ya and Yw. The mean values for SMZ V were lower for all three variables: 81.7 Mg ha^{-1} for Yw, 60.6 Mg ha^{-1} for Ya, and 798 mm for Eta (Figure 3). The yield gap, defined as the difference between Yw and Ya, was also higher in the best soils (38 Mg ha^{-1}) than in the worst soils (21 Mg ha^{-1}) (Figure 3).

The WPa exhibited a range of 32 to 186 Mg ha^{-1} mm^{-1}, with a degree of interannual variation (CV) of 21 % (Figure 4). The WPw ranged from 42 to 204 Mg ha^{-1} mm^{-1}, with an average of 121.4 Mg ha^{-1} mm^{-1}, approximately 1.5 times higher than the averaged WPa. CV = 15 % (Figure 5).

The E factor, which encompasses significant management practice variables such as planting date, harvest date, vinasse, and crop cycle, accounted for 40.5 % of the total variance throughout the period (Table 4). In contrast, weather variables (including rainfall, incident solar radiation, minimum and maximum air temperature) accounted for 46.2 %. Of these, rainfall was the main factor, accounting for 29.5 %, followed

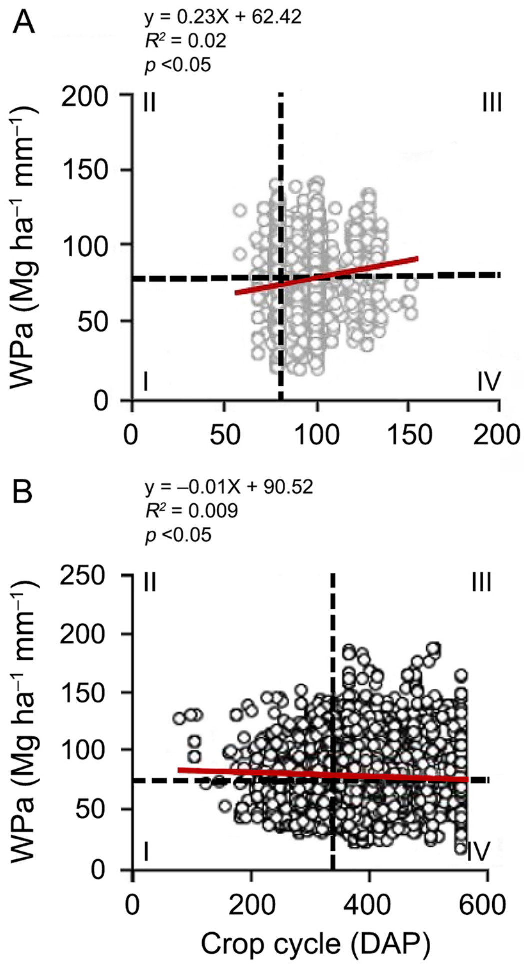

Figure 2 – Relationship between actual water productivity (WPa) and management practices factors. A) Vinasse, and B) crop cycle (DAP). Red solid lines are the function of linear regression, and the vertical dashed lines represent mean values of WPa, while horizontal dashed lines mean values represent mean values of management practice factors. R^2 is the coefficient of determination. Each quadrant represents a combination of the two variables analyzed in each panel. The dotted lines indicate the median of each variable. DAP = days after planting.

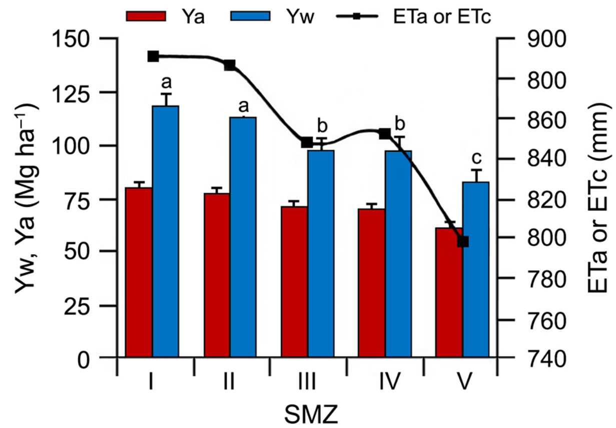

Figure 3 – Actual yield (Ya) and water-limited potential yield (Yw) in function of plots across soil management zones, from the best soil management zones (SMZ) (I) to the worst (V) and actual evapotranspiration (ETa) or crop evapotranspiration (ETc) (mm), during the on-farm sugarcane growing cycle. Different letters above the bars indicate statistically significant differences (Tukey's test, $p < 0.05$).

Table 4 – Contribution rates (*E*) of driving factors to the changes in actual water yield.

Factor	*E*
	%
Rainfall	29.5
Maximum temperature	4.1
Minimum temperature	1.1
Incident solar radiation	11.5
Soil management zone	13.3
Planting date	2.8
Harvest date	10.6
Crop Cycle	22.6
Vinasse	4.5

by solar radiation (11.5 %), minimum temperature (1.1 %), and maximum temperature (4.1 %). The SMZ represented 13.3 % of the variability (Table 4).

The E factor exhibited considerable variation across different growing seasons, with rainfall levels ranging from 20 % (in 2013) to 41 % (in 2014) (Figure 6). The maximum temperature exhibited an average increase of 8 %, ranging from 13 % (2013) to 7 % (2017). Conversely, the minimum temperature demonstrated a slight decline from 4 % (in 2013) to 8 % (in 2017). Compared to SMZ, the E factor ranged from 16 % (in 2013) to 9 % (in 2017). Among the management practice factors, the crop cycle exhibited the highest E, with an average of 18 %. These values increased from 15 % to 17 % between 2013 and 2017. Vinasse exhibited the lowest E average (5 %), ranging from 10 % (2013) to 1 % (2017). However, the planting date showed an E average of 8 %, ranging from 1 % (2013) to 12 % (2017). The harvest date exhibited a slight decrease of E from 11 % (in 2013) to 10 % (in 2017), with an average of 8 % (Figure 6).

Discussion

The results of the study indicate that management practices exerted a significant influence on WP values (Table 3), and thus should be considered as a potential avenue for enhancing WP in sugarcane plantations. The regression analyses of WP with crop cycle and vinasse (Table 3 and Figure 2A) demonstrate that ETa exerted a more significant influence than Yw and Ya on the composition of WP values. The ETa increased at a higher rate than Yw and Ya with the crop cycle, thereby demonstrating an inverse

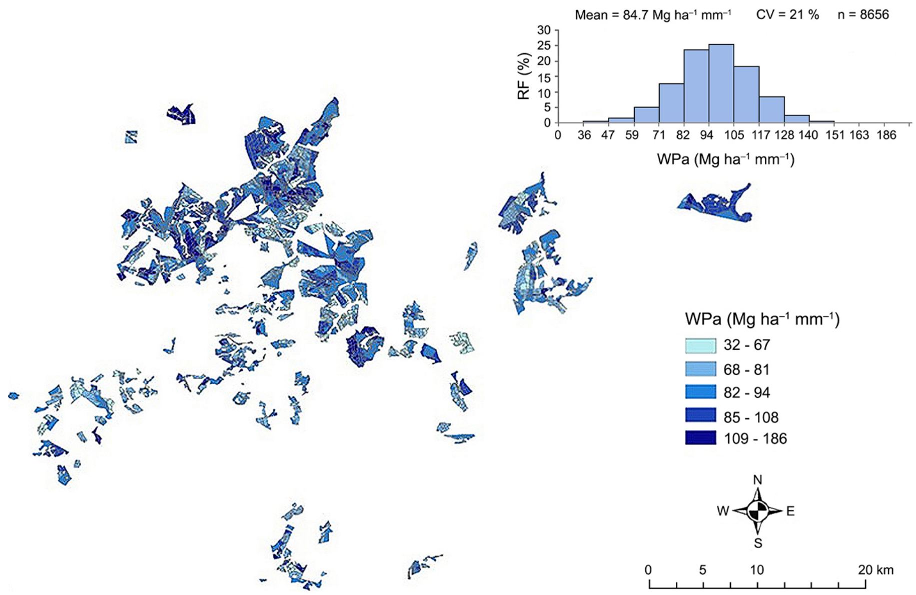

Figure 4 – Spatial variation of sugarcane actual water productivity (WPa) and its relative frequency (RF %) distribution over the plots from the 2013 to 2017 growing season. Mean, degree of interannual variation (CV %), and number of plots (n) are shown.

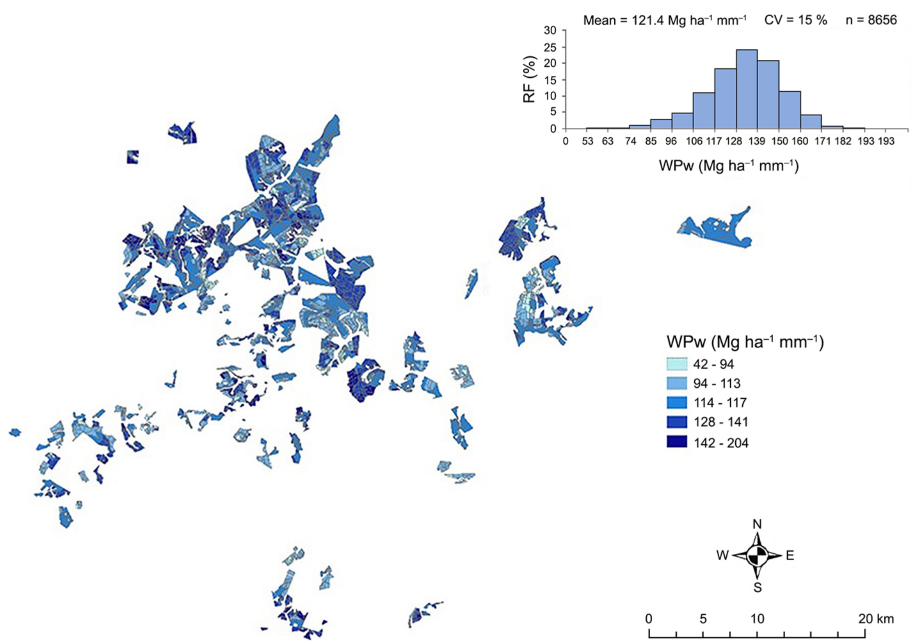

Figure 5 – Spatial variation of sugarcane attainable water productivity (WPw) and its relative frequency (RF %) distribution across the plots from the 2013 to 2017 growing season. Mean, degree of interannual variation (CV %), and number of plots (n) are shown.

relationship between WPa and WPw and these factors (Figure 2A). This highlights the interconnection between ETa, WPa, and management practices, emphasizing the pivotal role of crop management in defining of crop water use in sugarcane plantations in Brazil (Scarpare et al., 2016b).

Vinasse represents a nutrient-recovery strategy for reducing reliance on synthetic fertilizers (Sadeghi et al., 2016), while also serving as an important source of water. This is evidenced by the direct correlation between the increase of ETa and WPa (Figure 2A). Vinasse has been demonstrated to enhance soil moisture and promote crop growth during reduced precipitation, while also improving chemical soil properties (Reyes-Cabrera et al., 2017). The application of vinasse has been shown to significantly influence the reduction of runoff and soil loss, enhancing soil structure through particle aggregation (Tejada and Gonzalez, 2006), thus contributing to an increase in WPa.

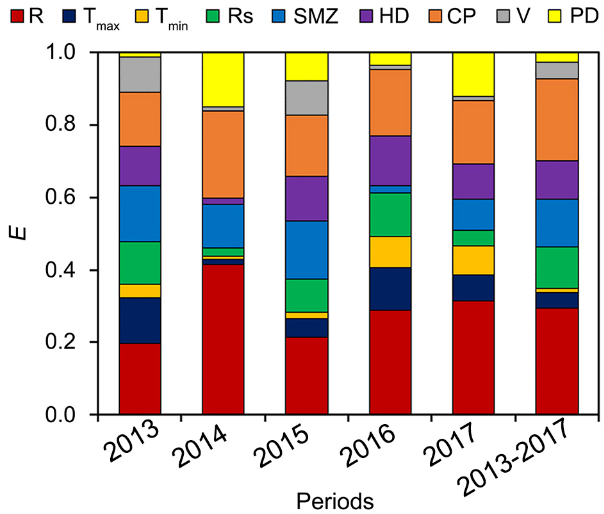

Figure 6 – Proportions of the contribution rates (E) of each driving factors in different periods. R = rainfall; T_{max} = maximum and T_{min} = minimum temperature; Rs = incident solar radiation for period; SMZ = soil management zone; HD = harvest date; CP = cultivation period; V = vinasse; PD = planting date.

The literature on sugarcane, employing diverse techniques and methodologies to estimate WPa for farming systems in Brazil and Thailand, has documented a WPa range of 28 to 65 Mg ha^{-1} mm^{-1} (Cabral et al., 2013; Teixeira et al., 2016; Chooyok et al., 2013). The WPa (84.7 Mg ha^{-1} mm^{-1}) observed in this on-farm study was approximately two times higher than the global average. However, in our research, in addition to the factors listed by the aforementioned authors (weather, soil, and planting date), we identified other management practices that affect WPa.

The analysis revealed that weather variables and SMZ exhibited relatively stable patterns across the period analyzed (CV = 8 % and 2 %, respectively). This is consistent with previous research on the relationship between weather and sugarcane Ya (Marin et al., 2008; Marin and Carvalho, 2012; Marin, 2016). These studies have identified weather variables as a significant explanatory factor for approximately 50 % of the total Ya variability in the southern region of Brazil. Furthermore, the SMZs were found to influence WPa determination. Sugarcane cultivation in poor soils, which exhibit low water retention, aluminum toxicity, and/or a reduction in nutrient availability (Otto et al., 2011), demonstrated lower Ya compared to the optimal SMZs (Figure 3). Other studies have investigated the impact of SMZs on WPa, demonstrating a trend of WPa being higher in better SMZs, which are known to be associated with fertile and well-structured soils (Mbava et al., 2020; Mojid et al., 2012; Russell, 2002).

In 2014, the southern region of Brazil experienced a severe drought, during which precipitation levels were significantly below the historical average. This resulted in a reduction of 6.5 % in WPa at the mill (Figure 6). Notably, in 2014, the rainfall exhibited the highest E value among the analyzed seasons. In contrast, in 2015, when rainfall was not a limiting factor for Ya, management factors played a significant role in explaining Ya variability (Figure 6). The instability of management practice factors across the years highlights the changes in the quality of these practices across seasons (Figure 6). This is crucial information for understanding the operational level of a mill and the consistency of technological investments across seasons (Millington, 2018).

Despite the considerable variation in average E from 2013 to 2017, our findings indicate that management practice factors were responsible for approximately 41 % of the total variability in WPa (Table 4 and Figure 6). On average, E for weather variables was just 5 % higher than that for management factors, highlighting the importance of management practice factors in WPa variation.

This study assessed the influence of significant driving factors on WPa, demonstrating that on-farm data can be utilized to determine the impact of crop management. Furthermore, it delineated methodologies for enhancing WPa in rainfed sugarcane cultivation systems in Brazil, encompassing approximately 90 % of the country's sugarcane growing area. However, in such farming systems, water availability represents a primary source of interannual yield fluctuations and yield differences among soil types.

Weather conditions were the primary cause of WPa variation during the period 2013-2017. However, management practice factors were identified as the predominant contributing factor, accounting for 40 % of the observed WPa variation during the 2015 season. The results indicate that improving management practices could potentially enhance WPa, given that soil and weather variables exhibited relatively consistent patterns across the years. Furthermore, management practices demonstrated the highest degree of interannual variation, underscoring their pivotal role in WPa variability.

Authors' Contributions

Conceptualization: Marin FR, Rosa JM. **Formal analysis:** Rosa JM, Marin FR. **Funding acquisition:** Marin FR. **Methodology:** Marin FR, Rosa JM. **Writing-original draft:** Rosa JM. **Writing-review & editing:** Rosa JM, Marin FR.

Conflict of interest

Authors declare that they have no conflict of interest.

Data availability statement

Data will be made available upon request to authors.

Declaration of use of AI Technologies

The authors declare that they did not use AI in analyzing and writing the manuscript.

References

Allen RG, Pereira LS, Raes D, Smith M. 1998. Crop Evapotranspiration: Guidelines for Computing Crop Water Requirements. FAO Irrigation and Drainage Paper 56. FAO, Rome, Italy.

Alvares CA, Stape JL, Sentelhas PC, Gonçalves JLM, Sparovek G. 2013. Köppen's climate classification map for Brazil. Meteorologische Zeitschrift 22: 711-728. https://doi.org/10.1127/0941-2948/2013/0507

Berndes G. 2002. Bioenergy and water-the implications of large-scale bioenergy production for water use and supply. Global Environmental Changes 12: 253-271. https://doi.org/10.1016/S0959-3780(02)00040-7

Cabral OMR, Rocha HR, Gash JH, Ligo MAV, Ramos NP, Packer AP, et al. 2013. Fluxes of CO_2 above a sugarcane plantation in Brazil. Agricultural and Forest Meteorology 182-183: 54-66. https://doi.org/10.1016/j.agrformet.2013.08.004

Carr MKV, Knox JW. 2011. The water relations and irrigation requirements of sugar cane (*Saccharum officinarum*): a review. Experimental Agriculture 47: 1-25. https://doi.org/10.1017/S0014479710000645

Chooyok P, Pumijumnog N, Ussawarujikulchai A. 2013. The water footprint assessment of ethanol production from molasses in Kanchanaburi and Supanburi Province of Thailand. APCBEE Procedia 5: 283-287. https://doi.org/10.1016/j.apcbee.2013.05.049

Dalmolin RSD, Pedron FA, Azevedo AC, Miguel P, Sana RS. 2004. Correspondence between the Brazilian soil classification system (Embrapa, 1999), WRB (ISSSWG RB, 1998), and Soil Taxonomy (USDA, 1999) for the main soil units of Rio Grande do Sul = Correspondência entre o Sistema Brasileiro de Classificação de Solos (Embrapa, 1999), WRB (ISSSWG RB, 1998) e o Soil Taxonomy (USDA, 1999) para as principais unidades de solos do Rio Grande do Sul. Boletim Técnico UFSM. Available at: http://jararaca.ufsm.br/websites/classolos/download/Informes/Informe02.pdf. [Accessed July 23, 2023] (in Portuguese).

Farias-Ramírez AJ, Duarte SN, Moreno-Pizani MA, Costa JO, Barros THS, Coelho RD. 2024. Combined effect of silicon and nitrogen doses applied to planting furrows on sugar, biomass and energy water productivity of sugarcane (*Saccharum* spp.). Agricultural Water Management 296: 108796. https://doi.org/10.1016/j.agwat.2024.108796

Food and Agriculture Organization [FAO]. 2017. AQUASTAT, FAOs' information system on water and agriculture. Brazil: geography and population. Available at: http://www.fao.org/nr/water/aquastat/data/query/results.html [Accessed Feb 19, 2020]

Hellegers PJGJ, Soppe R, Perry CJ, Bastiaanssen WGM. 2009. Combining remote sensing and economic analysis to support decisions that affect water productivity. Irrigation Science 27: 243-251. https://doi.org/10.1007/s00271-008-0139-7

Hoogenboom G, Porter C, Boote K, Shelia V, Wilkens PW, Singh U, et al. 2019. The DSSAT crop modeling ecosystem. p. 173-216. In: Boote, K. Advances in crop modelling for a sustainable agriculture. Burleigh Dodds Science Publishing, Cambridge, UK. https://doi.org/10.19103/AS.2019.0061.10

Jones JW, Hoogenboom G, Porter CH, Boote KJ, Batchelor WD, Hunt LA, et al. 2003. The DSSAT cropping system model. European Journal of Agronomy 18: 235-265. https://doi.org/10.1016/S1161-0301(02)00107-7

Lata S. 2019. Measurement of agricultural productivity and water productivity of crops. p. 253-314. In: Nüsser, M. ed. Advances in Asian human-environmental research. Springer Nature, Switzerland. https://doi.org/10.1007/978-3-030-00952-6_6

Marin FR, Inman-Bamber G, Silva TGF, Vianna MS, Nassif DSP, Carvalho KS. 2020. Sugarcane evapotranspiration and irrigation requirements in tropical climates. Theoretical and Applied Climatology 140: 1349-1357 https://doi.org/10.1007/s00704-020-03161-z

Marin, FR. 2016. Understanding sugarcane production, biofuels, and market volatility in Brazil: a research perspective. Outlook on Agriculture 45: 75-77. https://doi.org/10.1177/0030727016649802

Marin FR, Thorburn PJ, Nassif DSP, Costa LG. 2015. Sugarcane model intercomparison: structural differences and uncertainties under current and potential future climates. Environmental Modelling & Software 72: 372-386. https://doi.org/10.1016/j.envsoft.2015.02.019

Marin FR, Ribeiro RV, Marchiori PER. 2014. How can crop modeling and plant physiology help to understand the plant responses to climate change? A case study with sugarcane. Theoretical and Experimental Plant Physiology 26: 49-63. https://doi.org/10.1007/s40626-014-0006-2

Marin FR, Jones JW. 2014. Process-based simple model for simulating sugarcane growth and production. Scientia Agricola 71: 1-16. https://doi.org/10.1590/S0103-90162014000100001

Marin FR, Carvalho GL. 2012. Spatio-temporal variability of sugarcane yield efficiency in the state of São Paulo, Brazil. Pesquisa Agropecuária Brasileira 47: 149-156. https://doi.org/10.1590/S0100-204X2012000200001

Marin FR, Lopes-Assad ML, Assad ED, Vian CE, Santos MC. 2008. Sugarcane crop efficiency in two growing seasons in São Paulo State, Brazil. Pesquisa Agropecuária Brasileira 43: 1449-1455. https://doi.org/10.1590/S0100-204X2008001100002

Mbava N, Mutema M, Zengeni R, Shimelis H, Chaplot V. 2020. Factors affecting crop water use efficiency: a worldwide meta-analysis. Agricultural Water Management 228: 105878. https://doi.org/10.1016/j.agwat.2019.105878

Mevik BH, Wehrens R. 2007. The pls package: principal component and partial least squares regression in R. Journal of Statistical Software 18: 1-23. https://doi.org/10.18637/jss.v018.i02

Meyer WS. 1977. The irrigation experience from Australia. p. 437-454. In: Keating BA, Wilson JR. eds. Intensive sugarcane production. CAB International, Wallingford, UK.

Millington N. 2018. Producing water scarcity in São Paulo, Brazil: the 2014-2015 water crisis and the binding politics of infrastructure. Political Geography 65: 26-34. https://doi.org/10.1016/j.polgeo.2018.04.007

Mojid MA, Wyseure GCL, Mustafa, SMT. 2012. Water use efficiency and productivity of wheat as a function of clay amendment. Environmental Control in Biology 50: 347-362. https://doi.org/10.2525/ecb.50.347

Oliveira LA, Miranda JH, Cooke RAC. 2018. Water management for sugarcane and corn under future climate scenarios in Brazil. Agricultural Water Management 201: 199-206. https://doi.org/10.1016/j.agwat.2018.01.019

Otto R, Silva AP, Franco HCJ, Oliveira ECA, Trivelin PCO. 2011. High soil penetration resistance reduces sugarcane root system development. Soil and Tillage Research 117: 201-210. https://doi.org/10.1016/j.still.2011.10.005

Prado H. 2005. Soils of Brazil: Genesis, Morphology, Classification, Survey, Soil Management = Solos do Brasil: Gênese, Morfologia, Classificação, Levantamento, Manejo de Solos. 4ed. H. do Prado, Piracicaba, SP, Brazil (in Portuguese).

Priestley CHB, Taylor RJ. 1972. On the Assessment of surface heat flux and evaporation using large-scale parameters. Monthly Weather Review 100: 81-92. https://doi.org/10.1175/1520-0493(1972)100<0081:otaosh>2.3.co;2

Reyes-Cabrera J, Leon RG, Erickson JE, Rowland DL, Silveira ML, Morgan KT. 2017. Differences in biomass and water dynamics between a cotton-peanut rotation and a sweet sorghum bioenergy crop with and without biochar and vinasse as soil amendments. Field Crops Research 214: 123-130. https://doi.org/10.1016/j.fcr.2017.09.012

Ritchie JT. 1998. Soil water balance and plant water stress p. 41-54. In: Tsuji GY, Hoogenboom G, Thornton PK. eds. Understanding options for agricultural production. Springer, Berlin, Germany. https://doi.org/10.1007/978-94-017-3624-4_3

Russell EJ. 2002. Conditions and Plants Growth. Daya Books, New Delhi, India.

Sadeghi SH, Hazbavi Z, Harchegani MK. 2016. Controllability of runoff and soil loss from small plots treated by vinasse-produced biochar. Science of The Total Environment 541: 483-490. https://doi.org/10.1016/j.scitotenv.2015.09.068

Santos, HG, Jacomine PKT, Anjos LHC, Oliveira VA, Lumbreras JF, Coelho MR, et al. 2018. Brazilian Soil Classification System. Embrapa Solos, Rio de Janeiro, RJ, Brazil.

Scarpare FV, Hernandes TAD, Ruiz-Corrêa ST, Kolln OT, Gava GJC, Santos LNS, et al. 2016a. Sugarcane water footprint under different management practices in Brazil: Tietê/Jacaré watershed assessment. Journal of Cleaner Production 112: 4576-4584. https://doi.org/10.1016/j.jclepro.2015.05.107

Scarpare FV, Hernandes TAD, Ruiz-Corrêa ST, Picoli MCA, Scanlon BR, Chagas MF, et al. 2016b. Sugarcane land use and water resources assessment in the expansion area in Brazil. Journal of Cleaner Production 133: 1318-1327. https://doi.org/10.1016/j.jclepro.2016.06.074

Silva VPR, Silva BB, Albuquerque WG, Borges CJR, Sousa IF, Dantas Neto J. 2013. Crop coefficient, water requirements, yield and water use efficiency of sugarcane growth in Brazil. Agricultural Water Management 128: 102-109. https://doi.org/10.1016/j.agwat.2013.06.007

Singels A, Jones M, van Den Berg M. 2008. DSSAT v4. 5-Canegro Sugarcane Plant Module. International Consortium for Sugarcane Modelling, Johannesburg, South Africa.

Snedecor GW, Cochran WG. 1982. Statistical Methods. lowa State University Press, Des Moines, IA, USA.

Souza AP, Gaspar M, Silva EA, Ulian EC, Waclawovsky AJ, Nishiyama Jr MY, et al. 2008. Elevated CO_2 increases photosynthesis, biomass and productivity, and modifies gene expression in sugarcane. Plant Cell Environment 31: 1116-1127. https://doi.org/10.1111/j.1365-3040.2008.01822.x

Teixeira AHC, Leivas JF, Ronquim CC, Victoria DC. 2016. Sugarcane water productivity assessments in the São Paulo state, Brazil. International Journal of Remote Sensing Applications 6: 84-95. https://doi: 10.14355/ijrsa.2016.06.009

Tejada M, Gonzalez JL. 2006. Effects of two beet vinasse forms on soil physical properties and soil loss. Catena 68: 41-50. https://doi.org/10.1016/j.catena.2006.04.025

United States Department of Agriculture [USDA]. 1999. Soil Taxonomy: A Basic System of Soil Classification for Making and Interpreting Soil Surveys. Available at: https://www.nrcs.usda.gov/sites/default/files/2022-06/Soil%20Taxonomy.pdf. [Accessed July 23, 2023]

Van Keulen H, Seligman NG. 1987. Simulation of Water Use, Nitrogen Nutrition and Growth of a Spring Wheat Crop. Pudoc, Wageningen, The Netherlands.

Walter A, Galdos MV, Scarpare FV, Leal MRLV, Seabra JEA, Cunha MP, et al. 2014. Brazilian sugarcane ethanol: developments so far and challenges for the future. Advances in Bioenergy: The Sustainability Challenge 3: 373-394. https://doi.org/10.1002/9781118957844.ch24