Simulation of different nitrogen fertilization strategies using management zones in sugarcane cultivation

G. V. Bedum[1]; J. P. Molin[1]; R. C. Filho[1]

[1]Laboratory of Precision Agriculture, "Luiz de Queiroz" College of Agriculture – University of São Paulo, SP, Brazil

A paper from the Proceedings of the
17th International Conference on Precision Agriculture and 11th Brazilian Congress on Precision and Digital Agriculture
13-16 July 2026
Porto Alegre, Brazil

Abstract.
Nitrogen plays a central role in sugarcane physiology, as it is a structural component of amino acids, proteins, nucleic acids, and chlorophyll, being essential for photosynthetic activity, leaf expansion, biomass accumulation, and stalk formation. Given its relevance, nitrogen management efficiency represents a central research topic in sugarcane, particularly in systems characterized by strong spatial heterogeneity, where soil physical–hydric attributes, fertility levels, and environmental limitations modulate crop response. In this study, five nitrogen fertilization strategies (S1–S5) were evaluated through process-based modeling using APSIM-Sugarcane, applied to Management Zones (MZs) previously delineated within four commercial sugarcane fields. The MZs were adopted as simulation units to incorporate the spatial heterogeneity of soil physical–hydric, topographic, and productivity attributes into the recommendation process. The strategies were structured to represent different conceptual premises. Strategy S1 assumed lower N supply in high-yield environments, whereas S2 followed the opposite principle, increasing rates according to simulated productivity. Strategies S3, S4, and S5 were based on linear extraction models, assuming that N demand increases proportionally with biomass accumulation, using coefficients of 1.0, 1.2, and 1.4 kg N Mg^{-1}, respectively. Strategy performance was evaluated over five consecutive cropping cycles using integrated agronomic, physiological, economic, and energy indicators. The strategies differed substantially in N input, with averages of 75–79 kg N ha^{-1} in S1 and S3, 102–127 kg N ha^{-1} in S4 and S5, and 250 kg N ha^{-1} in S2. Physiological indicators revealed greater N stress under S1 and S3, whereas S2, S4, and S5 reduced this limitation. Water stress was more intense in S2, associated with greater leaf expansion and water requirement. Yield was consistently lower in restrictive MZs, reflecting edaphic limitations, particularly related to soil physical–hydric constraints. On average, S2 achieved the highest yield, with a 21.8% increase compared with S1, while S4 and S5 surpassed S1 by 6.3% and 13.9%, respectively. In addition, strategies with higher N supply promoted greater residue return and favored humic C. The economic–energy assessment highlighted contrasts among productivity, fertilization cost, and energy-use efficiency. Strategy S2 achieved the highest production and revenue but was associated with the highest costs and embodied energy. Conversely, S5 presented substantially lower costs, resulting in a partial economic return close to that of S2 and greater attractiveness from a cash-flow perspective. Integrated analysis indicated higher relative responsiveness to N in more restrictive environments, supporting the conceptual premise of S1, although the coefficients adopted were insufficient to meet physiological demand. Under the simulated conditions, the linear strategies S4 and S5 showed the best balance among application

rate, physiological stability, agronomic performance, and economic–energy viability. Overall, process-based modeling within MZs proved useful for comparing nitrogen fertilization strategies, identifying plausible N rate ranges, and supporting the preliminary design of on-farm experiments.

Keywords.
Site-specific management, agronomic optimization, agronomic modeling

1. Introduction

Sugarcane is an important industrial crop, recognized for its high yield potential, broad adaptability, and strategic importance across multiple agro-industrial value chains. Used to produce sugar, ethanol, bioelectricity, and several industrial co-products, sugarcane plays a central role in both energy security and the economic sustainability of many tropical regions (de Matos et al. 2020). Brazil is the world's leading producer, accounting for approximately 40% of global production. In 2024, national production reached 759.6 million megagrams over 10.05 million hectares of harvested area, with the state of São Paulo standing out as the main producing region (IBGE 2025). Despite this expressive production volume, the national average yield, estimated at 73.8 Mg ha^{-1}, still indicates a substantial gap relative to the crop's yield potential (FAO 2025).

Among the factors controlling sugarcane performance, nitrogen (N) stands out as one of the most demanded nutrients by the crop and is frequently one of the main yield-limiting factors, particularly in highly weathered tropical soils (Vitti et al. 2015). In plant metabolism, N is involved in the composition of amino acids, proteins, nucleic acids, and chlorophyll, being essential for photosynthetic activity, vegetative growth, sprouting, and stalk formation (Zeng et al. 2020). Nitrogen deficiency, especially during early growth stages, reduces leaf expansion, limits the interception of photosynthetically active radiation, and constrains biomass accumulation, with negative effects on yield and the technological quality of stalks (Franco et al. 2011; Zeng et al. 2020). Despite its importance, fertilizer management in sugarcane has traditionally relied on uniform nutrient application rates, disregarding the spatial variability inherent to commercial fields. In heterogeneous environments, this approach tends to result in under-application in areas with higher yield potential and over-application in zones with lower crop response (Nawar et al. 2017), compromising fertilizer agronomic efficiency, economic returns, and the environmental sustainability of the production system (Colaço et al. 2024; de Lara et al. 2023; Sanches et al. 2021).

In this context, Precision Agriculture (PA) provides tools to adjust input management to the spatial variability of cropping systems, improving the match between nutrient supply and crop demand (Mulla 2013). Among these strategies, the delineation of management zones (MZs) stands out. MZs are subareas with relative homogeneity in soil, topographic, and yield-related attributes, which support the interpretation and simplification of spatial variability (Molin et al. 2015). Therefore, in addition to optimizing sampling procedures and fertilizer recommendations (Nawar et al. 2017), MZs provide a more stable basis for model application by reducing spatial noise and computational complexity (Leo et al. 2023).

The evaluation of different fertilization strategies is essential for understanding crop responses to management practices (Sanches et al. 2021). In this regard, process-based modeling is a promising approach, as it simulates crop development, N dynamics within the soil–plant–atmosphere system, and management effects under contrasting soil and climate conditions (Carberry et al. 2009). In addition to anticipating crop responses and supporting the interpretation of relationships among variables, modeling can also contribute to the planning and targeting of field-based experimentation (Lawes et al. 2019). Among the available models, APSIM-Sugarcane stands out for integrating plant morphophysiological processes with soil water and nutrient dynamics, enabling the assessment of sugarcane performance under different environmental conditions and management strategies (Dias et al. 2021; Keating et al. 1999).

The integration of MZs and agronomic modeling may constitute a promising approach to comprehensively investigate the effects of contrasting N fertilization strategies, considering not only agronomic aspects but also the economic and energy impacts associated with sugarcane production (Leo et al. 2023). Conventional strategies are based on the assumption of a direct relationship between expected yield and N requirement, resulting in increasing N rates as yield potential increases (Stanford 1973). In contrast, alternative approaches propose reducing N rates in areas with higher intrinsic productivity, based on the hypothesis that more fertile soils can substantially contribute to the natural supply of nitrogen (Sanches and Otto 2022). Thus, the comparative simulation of these strategies can provide support for improving N management and for planning more targeted on-farm experimentation. Therefore, this study aimed to conduct an exploratory assessment, using process-based modeling, of the impact of contrasting N fertilization strategies applied to MZs in sugarcane, integrating agronomic, economic, and energy indicators.

2. Materials and methods

2.1. Study areas, input data, and management zone delineation

The study was conducted in four commercial sugarcane fields located in the state of São Paulo, Brazil, with areas ranging from 86 to 342 ha (Figure 1). The region has an Aw climate, classified as tropical with a dry winter according to the Köppen classification, with a rainy season from November to April and a dry season from May to September (Alvares et al. 2013). Mean annual precipitation ranges from 1,258 to 1,345 mm, and mean annual temperature ranges from 21.6 to 22.3 °C. The predominant soils are Oxisols and Ultisols, with medium to sandy texture.

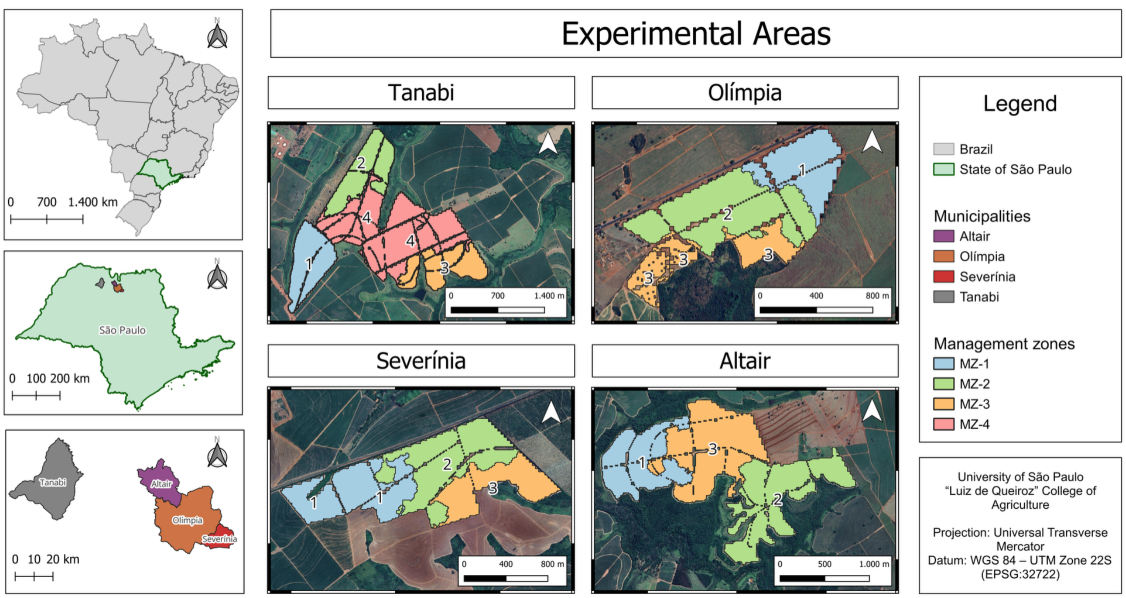

Fig. 1 Location of the experimental sugarcane fields included in the study.

The database integrated information on soil chemical properties, production environment, yield, topography, climate, and soil physical-hydric attributes used to represent the simulation conditions. Soil sampling was performed using an irregular grid, with a density of one sampling point every 3 ha. Composite samples were collected from the 0–0.25 m and 0.25–0.50 m layers and subsequently analyzed for the main chemical attributes, including soil organic matter, pH, P, K, Ca, Mg, Al, cation exchange capacity, base saturation, and S. Yield data were obtained from harvesters equipped with yield monitors, considering the 2021/22 to 2024/25 growing seasons. Raw data were filtered using MapFilter 2.0 (Maldaner et al. 2022), adopting a 40% variation threshold relative to the median and a 10% local filtering criterion, with a spatial-dependence distance of 20 m.

Daily weather series were obtained from the NASA POWER platform (Stackhouse Jr et al. 2015), whereas elevation data were derived from the ALOS PALSAR digital elevation model (Shimada and Osawa 2012). Because complete soil physical-hydric characterization was not available for the study areas, the soil profiles used in APSIM were defined based on the HYBRAS database (Ottoni et al. 2018), considering available observations for equivalent soil classes in the state of São Paulo. For each soil class, mean values of texture, bulk density, field capacity, permanent wilting point, and saturation were estimated. However, when different MZs had the same soil class but belonged to contrasting production environments, a 5% reduction in water availability was applied to the more restrictive environments. This adjustment was exploratory in nature and aimed to increase the edaphic differentiation among the simulated units.

Management zones were delineated by integrating yield data from two growing seasons with topographic and soil organic matter layers. All input layers were standardized to a 10 m spatial resolution and clipped to the boundary of each field before multivariate clustering. Initially, yield maps were assessed for temporal stability by classifying pixels into yield terciles and estimating their spatial consistency across growing seasons. Yield data and auxiliary variables were then organized into a standardized matrix, from which the spatial association between crop response and each environmental variable was assessed using bivariate Moran's (Wartenberg 1985). The number of clusters was defined based on successive k-means partitioning, considering the Fuzzy Performance Index and the Normalized Classification Entropy (Miranda et al. 2021). After classification, the clusters were converted into vector polygons. The MZs were subsequently adopted as spatial simulation units, allowing the evaluation of N fertilization strategies to incorporate the different soil physical-hydric, topographic, chemical, and yield-related conditions present within the fields.

2.2. Simulation of nitrogen fertilization

Simulations were performed using the mechanistic APSIM model, Agricultural Production Systems Simulator, with the Sugarcane module (Keating et al. 1999). Soil water dynamics were simulated using the SoilWat module, whereas carbon and nitrogen transformation processes were represented by the SoilN and SurfaceOrganicMatter modules, including mineralization, immobilization, residue decomposition, and interactions with crop growth. The simulations integrated daily weather series, chemical, organic, and physical-hydric soil attributes by MZ, as well as management information. For the chemical and organic attributes required by the model, a vertical gradient based on exponential decay was adopted for subsurface layers, representing the natural decrease in fertility and organic matter with soil depth (Sisti et al. 2004). Soil organic matter contents were converted into organic carbon using the Van Bemmelen factor, assuming 58% carbon in organic matter (Nelson and Sommers 1996).

The simulated cultivar was RB867515, with genetic coefficients and physiological parameters defined according to Dias (2020). The cropping system was represented with 1.5 m row spacing, a density of 15 stalks m^{-2}, and no irrigation. The planting date was fixed at March 15, with a 510-day plant cane cycle followed by four ratoon cycles of 380 days each. Although the available soil data and yield history corresponded to the recent period, from 2021 onward, these data were used to initialize the simulations in 2019, allowing the representation of five complete production cycles using observed weather series.

Five N prescription strategies were evaluated, in which N rates were defined based on the simulated yield of the previous cycle (Table 1). Strategy S1 was based on the approach described by Sanches and Otto (2022), adopting an inverse relationship between yield and N requirement. This approach assumes that environments with higher yield potential may have a greater soil contribution to the natural supply of N, thereby reducing the relative dependence on mineral fertilizer (Thorburn et al. 2017). Strategy S2 was defined as the inverse form of S1, maintaining the same upper and lower limits of specific N requirement, but increasing the relative N input as yield increased. This formulation was adopted to represent the conventional premise of progressive recommendation, according to which more productive environments require greater

N supply (Stanford 1973). Additionally, three strategies based on linear N extraction coefficients, frequently used as references in the Brazilian context, were evaluated (Amaral et al. 2015). In these strategies, N demand was proportional to simulated yield, considering factors of 1.0, 1.2, and 1.4 kg N Mg^{-1} of stalks for S3, S4, and S5, respectively.

Table 1. Equations of the nitrogen fertilization factor (FN, kg N Mg^{-1}) as a function of crop yield (Y, Mg ha^{-1}) for the five fertilization strategies evaluated.

Strategies	Equations
S1	$F_N = 2.8889 - 0.032 \times Y + 0.0001 \times Y^2$
S2	$F_N = 0.3289 + 0.032 \times Y - 0.0001 \times Y^2$
S3	$F_N = 1.0$
S4	$F_N = 1.2$
S5	$F_N = 1.4$

2.3. Agronomic, economic, and energy-related aspects

Model outputs were organized into agronomic, economic, and energy indicators. Agronomic performance was characterized by yield, expressed in Mg ha^{-1}, and total sugar content. To interpret the mechanisms underlying yield responses, stress factors associated with N deficiency and water deficit were analyzed, considering their effects on photosynthesis and leaf expansion. Soil carbon dynamics were assessed based on the fluxes simulated by the SoilN and SurfaceOrganicMatter modules.

Energy performance was evaluated through embodied energy, expressed as MJ kg^{-1}, calculated as the ratio between total energy input and yield. The energy associated with N fertilization was estimated by considering the rates applied per hectare in each year, multiplied by the respective energy coefficient described in Table 2. Energy consumption associated with fuel use was determined from the product of hourly fuel consumption, effective field capacity, and the energy index. Machinery depreciation was calculated as a function of equipment service life and mass. Energy consumption associated with labor was estimated considering only the working time required.

Table 2. Energy indices for the inputs used in the production system.

Energy input	Unit	Energy index (MJ $unit^{-1}$)	Reference
Nitrogen (N)	kg	74	Pellizzi (1992)
Labor	h	2.2	Ferraro Jr (1999)
Fuel	L	45.7	Boustead and Hancock (1979)
Machine depreciation	kg	32.5	Mantoam et al. (2016)

Gross revenue was estimated as the product of simulated yield and the sugarcane price per Mg observed in the respective harvest month. Partial economic return was calculated as the difference between gross revenue and the total fertilization cost. All monetary values used in the economic analysis were adjusted for inflation using the IGP-M index (IPEA 2025) and expressed as present values as of October 2025. The price of N fertilizer was obtained from the annual average reported by CONAB (2025). After inflation adjustment, values in Brazilian reais were converted to US dollars using an exchange rate of BRL 5.32 per USD 1.00, corresponding to October 1, 2025.

Total fertilization cost was estimated by combining N fertilizer expenditure and application costs, including labor, machinery operation, fuel consumption, maintenance and repairs, and fixed machinery costs (Equations 1–6). Fixed costs included depreciation, interest, insurance, and other ownership-related charges. Machinery purchase values were US$ 131,578.00 for the tractor and US$ 11,278.00 for the fertilizer applicator, according to supplier data. Useful life was set at 12,000 h for the tractor and 2,400 h for the fertilizer applicator. The residual value was assumed to be 30% of the initial purchase value. Maintenance and repair costs were estimated as 95% of the average machinery value over its useful life (ASABE 2011), whereas insurance and taxes were assumed to correspond to 1.0% of the annual average machinery value.

[1] $\mathrm{TFC} = \mathrm{FC} + \mathrm{AC}$

[2] $\mathrm{AC} = (\mathrm{LC} + \sum_n \mathrm{MOC}) \times \alpha$

[3] $\mathrm{MOC_n} = (\mathrm{FCC_n} + \mathrm{MR_n} + \mathrm{FHC_n})$

[4] $\mathrm{FCC_n} = \mathrm{TP} \times \mathrm{S} \times \mathrm{DP}$

$$[5]\quad MR_n = \frac{95\% \times IV}{t}$$

$$[6]\quad FHC = \frac{\left(IV \times \left(\left[\frac{(1-RV)}{b}\right] + \left[\frac{(1+RV)}{2} \times i\right] + FAI\right)\right)}{t}$$

Where: TFC represents the total fertilization cost (US$ ha⁻¹); FC, N fertilizer cost (US$ ha⁻¹); AC, fertilizer application cost (US$ ha⁻¹); LC, labor cost (US$ 4.70 h⁻¹, average wage practiced in the region); MOC, hourly machinery operating cost (US$ h⁻¹); n, number of implements, such as the tractor and the fertilizer spreader; α, operational field-time coefficient (0.39 h ha⁻¹); FCC, fuel consumption cost (US$ h⁻¹); MR, maintenance and repair cost (US$ h⁻¹) (ASABE 2011); FHC, fixed hourly cost (US$ h⁻¹) (Milan and Rosa 2015); TP, tractor power (150 cv); S, fuel consumption rate (0.121 cv⁻¹ h⁻¹) (ASABE 2011); DP, average diesel price in the year (ANP 2025); IV, initial machinery value (US$); RV, residual value, expressed as a decimal fraction of the initial value (Milan and Rosa 2015); b, useful life of the asset in years; t, useful life of the asset in hours; i, interest rate, fixed at 13.90% per year (IPEA 2025); and FAI, shelter, insurance, and taxes factor, expressed as a decimal.

Statistical comparisons were performed to support the exploratory interpretation of differences among the simulated nitrogen fertilization strategies. All data obtained from the simulations were checked for the assumptions of normality and homogeneity of variance using the Shapiro–Wilk and Levene tests, respectively. Once these assumptions were met, analysis of variance (ANOVA) was performed at a 5% significance level. When significant effects were detected, means were compared using Tukey's test ($p < 0.05$). All statistical analyses were conducted in RStudio.

3. Results and discussion

3.1. Agronomic and physiological assessment

The nitrogen prescription strategies generated a gradient in N supply, with direct consequences for the simulated stress indicators (Figure 2). S2 showed mean N rates close to 250 kg N ha⁻¹ and a wide range of variation (103–389 kg N ha⁻¹), whereas S1 and S3 had the lowest N inputs, approximately 75 and 79 kg ha⁻¹, respectively, which are below the ranges commonly adopted in Brazilian commercial systems (Quaggio et al. 2022). S4 and S5 occupied an intermediate position, with mean N rates of approximately 102 and 127 kg ha⁻¹, respectively. This gradient directly affected the N stress indicators, as the strategies with higher N supply, particularly S2, reduced N limitation on photosynthesis and leaf expansion (Bassi et al. 2018). This response is consistent with the role of N in chlorophyll formation and in the synthesis of proteins and enzymes associated with carbon metabolism and vegetative growth in sugarcane (Zeng et al. 2020). In contrast, S1 and S3 maintained greater physiological restriction, suggesting that the coefficients used in these recommendation strategies underestimated crop N demand under the simulated conditions.

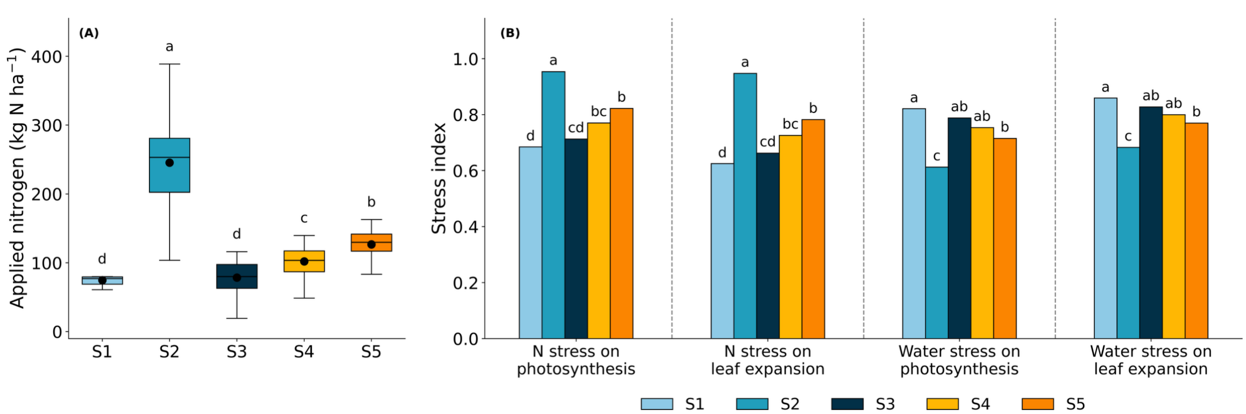

Fig. 2 Applied nitrogen rate (A) and stress indicators (B). Strategies followed by different letters differ statistically by Tukey's test at the 5% significance level.

However, the lower N limitation observed in S2 did not result in a better physiological balance of the crop. Considering that values close to 1 indicate lower restriction, S2 showed low N limitation for photosynthesis (0.954) and leaf expansion (0.948), but simultaneously recorded the lowest water stress factors for these processes (0.613 and 0.683, respectively), indicating greater water limitation. This pattern suggests that the higher N supply stimulated canopy development and increased transpiration demand (Dinh et al. 2017; Sun et al. 2025), shifting part of the yield limitation from nutrition to soil water availability. In turn, S4 and S5 occupied an intermediate position, reducing N limitation without proportionally intensifying water stress, reinforcing that sugarcane response to N is mediated by the interaction between nutrition and soil water availability (Wiedenfeld 2000).

This physiological balance was reflected in crop development (Figure 3). S2 showed the highest mean yield (89 Mg ha⁻¹), differing from S1, S3, and S4, confirming that reduced N limitation favored crop development (Gopalasundaram et al. 2012; Zeng et al. 2020). However, the yield gain was not proportional to the increase in N input, as S5 reached 83 Mg ha⁻¹, a value statistically similar to that of S2, even with less intensive fertilization. This result indicates a reduction in the efficiency of the applied N rate, since, as N limitation decreased, other factors, particularly soil water availability, became more restrictive to yield response (Boschiero et al. 2020; van Ittersum and Rabbinge 1997). The lower yields observed in S1 and S3, approximately 73 and 70 Mg ha⁻¹, respectively, reinforce that conservative strategies may constrain growth when N supply does not match the physiological demand of the crop, especially under conditions in which soil mineralization is insufficient to sustain low fertilizer inputs (Cui et al. 2008; Franco et al. 2011).

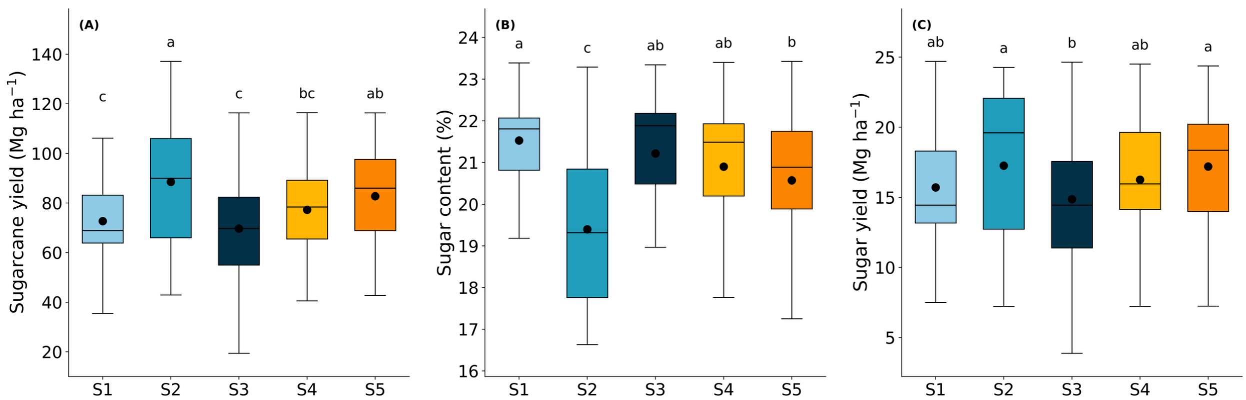

Fig. 3 Sugarcane yield (A), stalk sugar content (B), and sugar yield per hectare (C). Strategies followed by different letters differ statistically by Tukey's test at the 5% significance level.

The sugar content showed an inverse trend relative to yield (Figure 3). Although S2 achieved the highest yield, it recorded the lowest mean sugar content (19.4%), approximately 2.1 percentage points below S1 (21.5%). This pattern is consistent with the sucrose dilution effect associated with excessive vegetative growth and greater photoassimilate allocation to canopy expansion (Franco et al. 2011; Yang et al. 2013). In S1, the higher percentage sugar content did not translate into greater production per area, as the lower stalk yield limited total sugar accumulation. When sugar content was integrated with yield, the differences were partially offset. S2 and S5 showed the highest absolute sugar yield per hectare, with 17.26 and 17.20 Mg ha⁻¹, respectively, whereas S3 had the lowest performance (14.86 Mg ha⁻¹). Thus, the higher yield of S2 compensated for its lower sugar concentration, while S5 achieved similar sugar production by combining high yield with a lower negative effect on the technological quality of the crop.

3.2. Simulated soil carbon dynamics

In the first cycle, humic C stocks showed marked reductions, with no statistical differences among strategies, indicating that the initial dynamics were predominantly controlled by crop establishment rather than by N management (Meier and Thorburn 2016; Verburg et al. 2025). In the subsequent cycles, a gradual recovery of humic C was observed, with greater accumulation under the most productive strategies, particularly S2, followed by S5 and S4 (Figure 4). This pattern suggests that greater crop growth increased the return of plant residues to the soil, favoring C replenishment in more stable fractions (Sattolo et al. 2017). In contrast, S1 and S3 showed smaller increments, consistent with the yield restriction caused by lower N supply. However, S1 did not indicate progressive depletion of humic C. Therefore, although this strategy resulted in lower C accumulation compared with the more productive strategies, there was no evidence, over the five simulated cycles, of continuous impairment of the simulated humic compartment.

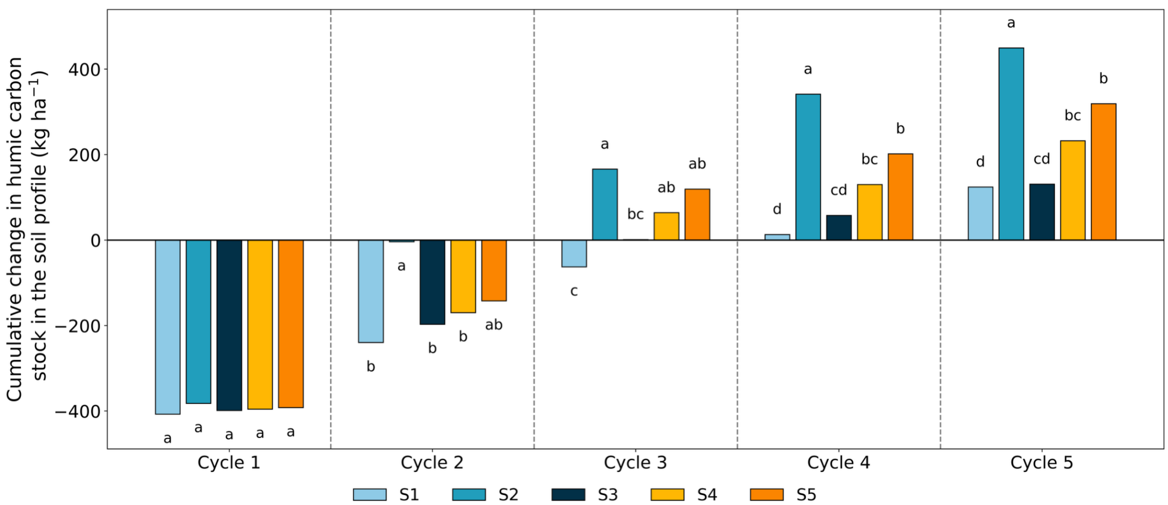

Fig. 4 Soil carbon dynamics relative to the simulated initial condition. Strategies followed by different letters differ statistically by Tukey's test at the 5% significance level.

3.3. Economic and energy assessment

The economic assessment showed that the greater yield performance of S2 resulted in the highest gross revenue, close to US$ 2,400 ha^{-1}, which was 28.6% higher than that of S3, the strategy with the lowest revenue (Figure 5). This result indicates that the greater N input was effective in increasing stalk yield and, consequently, gross return. However, this productive advantage was accompanied by the highest fertilization cost, which reached approximately US$ 381 ha^{-1}, nearly three times higher than that observed for S1 and S3. Thus, when gross revenue and fertilization cost were integrated into partial economic return, the superiority of S2 became less evident. Across the simulated cycles, S2 and S5 showed the highest absolute values, exceeding US$ 2,000 ha^{-1}, whereas S3 recorded the lowest performance, around US$ 1,726 ha^{-1}. S1 and S4 occupied an intermediate position, with partial returns close to US$ 1,822 and US$ 1,903 ha^{-1}, respectively, without statistical difference relative to S2 and S5.

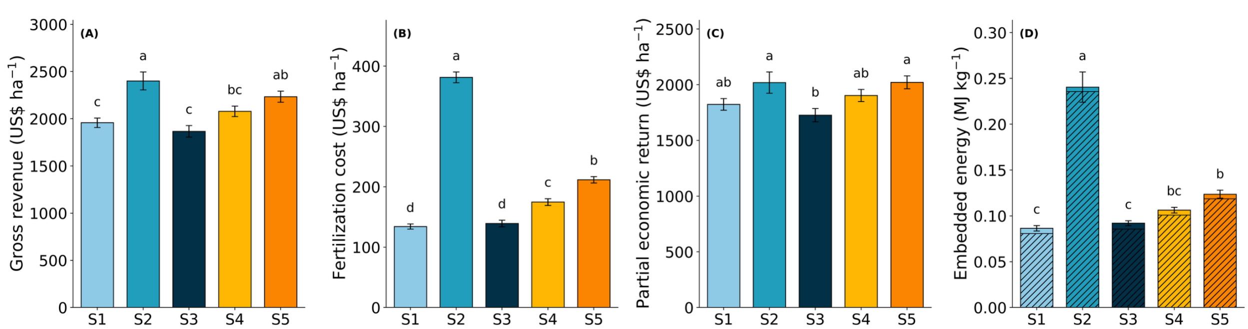

Fig. 5 Economic and energy indicators: (A) gross revenue, (B) fertilization cost, (C) partial economic return, and (D) embodied energy. In panel D, hatched bars indicate the contribution of nitrogen to total energy. Strategies followed by different letters differ statistically by Tukey's test at the 5% significance level.

The energy analysis reinforced the contrast between productive intensification and input-use efficiency. S2 showed the highest embodied energy per unit of stalk produced, close to 0.24 MJ kg⁻¹, differing statistically from the other strategies and exceeding by nearly threefold the values observed for S1 and S3. Although S2 achieved the highest yield, the gain in production was not sufficient to dilute the high energy demand associated with the greater N fertilizer input. Despite its higher values, the N-related energy input in S2 was above the value reported by Firouzi et al. (2022), 0.17 MJ kg^{-1}, but below that observed by Naseri et al. (2021), 0.27 MJ kg^{-1}, positioning this strategy within the range of energy intensification described for sugarcane. Among the simulated strategies, S4 and S5 showed intermediate energy intensities, close to 0.11 and 0.12 MJ kg^{-1}, respectively, maintaining a lower energy penalty. In turn, S1 combined the lowest fertilization cost and the lowest energy intensity, however, its partial economic return was approximately US$ 200 ha^{-1} lower than that of S2 and S5, although this difference was not statistically significant.

3.4. Integrated performance indicators

The integrated assessment showed that no strategy simultaneously maximized productive, physiological, economic, and energy-related indicators (Figure 6), indicating that N prescription involves trade-offs among yield, cost, physiological stress, and energy intensity (Sanches et al. 2021). S2 showed the highest agronomic performance, associated with greater yield and lower N limitation. However, this response required a higher fertilizer rate, increasing fertilization cost and embodied energy. Furthermore, this strategy requires greater fertilizer investment to sustain the production cycle, without resulting in a proportional advantage in partial economic return. Under real production conditions, this profile may be unfavorable, as it increases working capital requirements and exposure to volatility in input and commodity prices. Thus, the results do not support recommendations based on excessively high coefficients. From approximately 65.7 Mg ha^{-1} onward, the rate estimated by S2 exceeds 2 kg N Mg^{-1} of stalks, representing an unfavorable threshold under economic and energy criteria (Thorburn et al. 2017). In scenarios where risk management, capital optimization, and input-use efficiency are priorities, this strategy becomes less competitive.

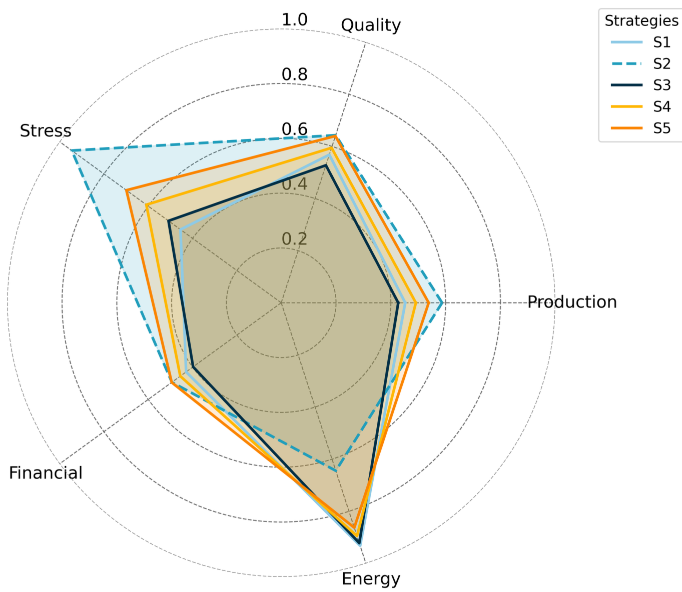

Fig. 6 Integrated performance of the management strategies across the five evaluated axes: production, quality, stress, energy, and financial performance, after indicator normalization. Higher values indicate better relative performance for each criterion.

In contrast, S1 showed greater physiological stress, particularly nutritional stress, reflecting insufficient N supply throughout the cycle (Gopalasundaram et al. 2012; Vitti et al. 2015). This response resulted in lower yield performance, although partial economic return did not differ markedly from the other strategies due to the lower fertilization cost. However, the energy balance was favorable, as the energy expenditure per unit produced was reduced, which was a direct consequence of the low input level. S3 showed a similar pattern, with low energy intensity, but lower yield, lower sugar production per area, and lower partial economic return.

Conversely, the coefficients used in S4 and S5 were more suitable for the simulated conditions, promoting greater synchrony between N supply and crop metabolic demand throughout the cycle. As a result, these strategies showed intermediate performance, with yield and sugar production per area close to those of S2, but with more favorable energy performance and similar financial competitiveness. Thus, under the evaluated conditions, S4 and S5 represent more balanced strategies, reconciling agronomic return with resource-use efficiency (Franco et al. 2011; Sanches et al. 2021).

3.5. Impact of nitrogen fertilization strategies under contrasting environments

Figure 7 shows the relative response to N in three contrasting management zones, calculated as the percentage yield increase relative to the condition without N application. The zones represent an edaphic–productive gradient, in which G3–MZ3 corresponds to the least restrictive condition, associated with an Ultisol in production environment B; G4–MZ1 represents an intermediate condition, characterized by an Oxisol in production environment C; and G4–MZ2 corresponds to the most yield-restrictive condition, associated with an Inceptisol in production environment E. In the environment with the highest yield potential, G3–MZ3, relative increments were lower and more stable across strategies, ranging from approximately 73 to 127%. This pattern suggests a greater capacity of this environment to sustain yield even under lower N inputs, possibly due to greater natural N availability and soil mineralization contribution, as well as lower leaching potential (Sanches and Otto 2022).

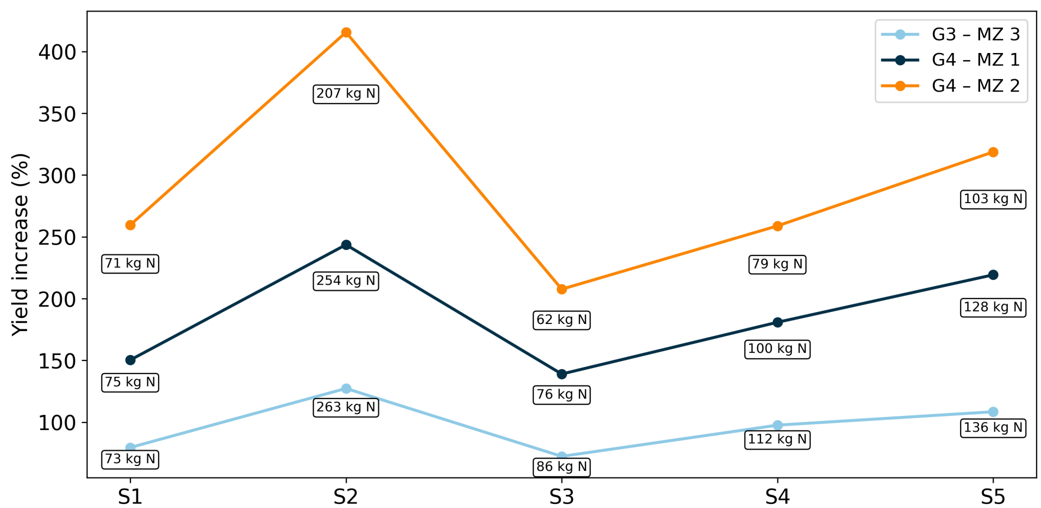

Fig. 7 Yield increase relative to the condition without nitrogen fertilization.

In the more restrictive environments, the relative response was more pronounced. In G4–MZ1, yield increments ranged from 139 to 244%, whereas in G4–MZ2 they reached up to 416% under S2. Therefore, in areas with lower baseline yield, N omission or reduction increases the gap between the natural soil N supply and the physiological demand of the crop (Sanches and Otto 2022). However, high percentage increments do not necessarily imply higher absolute yield, since these environments are also subject to simultaneous limitations related to soil, water, and fertility conditions (Dinh et al. 2017; Inman-Bamber 2013). The comparison between G4–MZ1 and G4–MZ2 reinforces that the response to N also varies within the same field, even under similar climatic conditions and general management. This difference indicates that N fertilization efficiency is not determined only by regional factors, but also by local edaphic attributes, such as fertility, water availability, and nutrient retention capacity (Sanches et al. 2019, 2021).

3.6. Future developments and implications for OFE

The simulation of N fertilization strategies showed potential to support the structuring of on-farm experiments, as it allows the anticipation of scenarios, the identification of treatments with greater potential to generate agronomic contrasts, and the evaluation of fertilization recommendations (Banerjee et al. 2025; Colaço et al. 2024; Verburg et al. 2025). By virtually testing increasing, decreasing, and linear N supply curves across different environments, modeling can preliminarily discriminate which strategies are more sensitive to soil and climate conditions, which tend to converge toward similar performance, and which pose a greater risk of under- or over-fertilization. Therefore, process-based modeling does not replace experimental validation, but expands the capacity for planning on-farm experimentation (Leo et al. 2023). The continuity of this study primarily depends on replacing standard physical-hydric soil profiles with profiles obtained directly from the experimental areas. The incorporation of field-observed data will allow a more accurate representation of the water balance, improving the estimation of water stress and N and C dynamics in the soil.

As a next step to strengthen the integration between on-farm experimentation and process-based modeling, simulations should be extended to longer time series. This approach would allow the fitting of local yield response functions and the estimation of agronomic and economic optimum N rates for each environment, making it possible to quantify the distance between the rates prescribed by each strategy and their respective local optima. In addition, it would enable the investigation of whether specific recommendation logics, such as decreasing curves, progressive curves, or linear extraction coefficients, are more suitable for particular soil conditions, yield potential levels, or water availability contexts. Thus, the combination of these tools can strengthen the development of more targeted recommendation systems, guided not only by expected yield but also by the local crop response to fertilization (Colaço et al. 2024; Lawes et al. 2019; Tanaka et al. 2026).

4. Conclusions

The results demonstrated that agronomic modeling was sensitive to differences among N fertilization strategies, allowing the identification of distinct responses under productive, physiological, economic, and energy-related criteria. Strategy S2 reduced N limitation and resulted in the highest yield. However, this gain was accompanied by greater water stress, higher fertilization cost, and greater embodied energy, reducing its advantage when economic and energy-related criteria were considered.

Strategies S1 and S3, in turn, showed lower fertilization costs and lower N-related energy use, but their low N inputs restricted crop growth, increased N stress, and reduced yield performance. In the case of S1, the results do not invalidate the conceptual rationale of reducing N rates in environments with higher yield potential. However, they indicate that the coefficients used were conservative for the simulated conditions, resulting in insufficient N supply. In contrast, S4 and S5 showed more balanced performance, with yield and sugar production close to those of S2, lower energy penalty, and similar partial economic return, representing more consistent alternatives for reconciling production, input-use efficiency, and financial performance.

Regarding the limitations and perspectives of the study, the results should be interpreted within the scope of an exploratory scenario analysis, rather than as a definitive validation of the evaluated strategies. Even so, the study demonstrates the potential of modeling as a preliminary step for planning on-farm experiments, allowing the selection of strategies with greater probability of generating measurable contrasts, the delimitation of plausible N rate ranges, and the formulation of more robust hypotheses for field validation. Thus, the integration of process-based modeling, management zones, and on-farm experimentation can support decision-making systems that are more sensitive to spatial variability and to the local crop response to fertilization.

5. References

Alvares, C. A., Stape, J. L., Sentelhas, P. C., Gonçalves, J. L. de M., & Sparovek, G. (2013). Köppen's climate classification map for Brazil. *Meteorologische Zeitschrift*, 22(6), 711–728. https://doi.org/10.1127/0941-2948/2013/0507

Amaral, L. R., Molin, J. P., & Schepers, J. S. (2015). Algorithm for Variable-Rate Nitrogen Application in Sugarcane Based on Active Crop Canopy Sensor. *Agronomy Journal*, *107*(4), 1513–1523. https://doi.org/10.2134/agronj14.0494

ANP. (2025). Agência Nacional do Petróleo, Gás Natural e Biocombustíveis. (National Agency of Petroleum, Natural Gas and Biofuels). *Série histórica de preços de combustíveis e de GLP*. https://www.gov.br/anp/pt-br/centrais-de-conteudo/dados-abertos/serie-historica-de-precos-de-combustiveis

ASABE - American Society of Agricultural and Biological Engineers. (2011). ASAE D497.7: *Agricultural machinery management data*. http://elibrary.asabe.org/abstract.asp?aid=36431&t=1&redir=&redirType=

Banerjee, K., Dutta, S., Das, S., & Sadhukhan, R. (2025). Crop simulation models as decision tools to enhance agricultural system productivity and sustainability – a critical review. *Technology in Agronomy*. https://doi.org/10.48130/tia-0024-0032

Bassi, D., Menossi, M., & Mattiello, L. (2018). Nitrogen supply influences photosynthesis establishment along the sugarcane leaf. *Scientific Reports*, *8*(1), 2327. https://doi.org/10.1038/s41598-018-20653-1

Boschiero, B. N., Mariano, E., Torres-Dorante, L. O., Sattolo, T. M. S., Otto, R., Garcia, P. L., et al. (2020). Nitrogen fertilizer effects on sugarcane growth, nutritional status, and productivity in tropical acid soils. *Nutrient Cycling in Agroecosystems*, *117*(3), 367–382. https://doi.org/10.1007/s10705-020-10074-w

Boustead, I., & Hancock, G. F. (1979). Handbook of industrial energy analysis. Chichester, UK: Ellis Horwood Ltd.

Carberry, P. S., Hochman, Z., Hunt, J. R., Dalgliesh, N. P., McCown, R. L., Whish, J. P. M., et al. (2009). Re-inventing model-based decision support with Australian dryland farmers. 3. Relevance of APSIM to commercial crops. *Crop and Pasture Science*, *60*(11), 1044–1056. https://doi.org/10.1071/CP09052

Colaço, A. F., Whelan, B. M., Bramley, R. G. V., Richetti, J., Fajardo, M., McCarthy, A. C., et al. (2024). Digital strategies for nitrogen management in grain production systems: lessons from multi-method assessment using on-farm experimentation. *Precision Agriculture*, *25*(2), 983–1013. https://doi.org/10.1007/s11119-023-10102-z

CONAB. (2025). Companhia Nacional de Abastecimento. (National Supply Company). *Preços*. https://www.gov.br/conab

Cui, Z., Zhang, F., Chen, X., Miao, Y., Li, J., Shi, L., et al. (2008). On-farm estimation of indigenous nitrogen supply for site-specific nitrogen management in the North China plain. *Nutrient Cycling in Agroecosystems*, *81*(1), 37–47. https://doi.org/10.1007/s10705-007-9149-8

de Lara, A., Mieno, T., Luck, J. D., & Puntel, L. A. (2023). Predicting site-specific economic optimal nitrogen rate using machine learning methods and on-farm precision experimentation. *Precision Agriculture*, *24*(5), 1792–1812. https://doi.org/10.1007/s11119-023-10018-8

de Matos, M., Santos, F., & Eichler, P. (2020). Chapter 1 - Sugarcane world scenario. In F. Santos, S. C. Rabelo, M. De Matos, & P. Eichler (Eds.), *Sugarcane Biorefinery, Technology and Perspectives* (pp. 1–19). Academic Press. https://doi.org/10.1016/B978-0-12-814236-3.00001-9

Dias, H. B. (2020). *Sugarcane variety trait modelling: Evaluating and improving the APSIM-Sugar model for simulating crop performance under current and future climates across Brazil* [Doctoral dissertation, Luiz de Queiroz College of Agriculture, University of São Paulo].

https://doi.org/10.11606/T.11.2020.tde-14082020-105124

Dias, H. B., Sentelhas, P. C., Inman-Bamber, G., & Everingham, Y. (2021). Sugarcane yield future scenarios in Brazil as projected by the APSIM-Sugar model. *Industrial Crops and Products*, *171*, 113918. https://doi.org/10.1016/j.indcrop.2021.113918

Dinh, T. H., Watanabe, K., Takaragawa, H., Nakabaru, M., & Kawamitsu, Y. (2017). Photosynthetic response and nitrogen use efficiency of sugarcane under drought stress conditions with different nitrogen application levels. *Plant Production Science*, *20*(4), 412–422. https://doi.org/10.1080/1343943X.2017.1371570

FAO - Food and Agriculture Organization of the United Nations. (2025). *Production: Crops and livestock products*. Food and Agriculture Organization of the United Nations. https://www.fao.org/faostat/en/#data/QCL

Ferraro Jr, L. A. (1999). An evaluation method of production systems and sustainability. Master's dissertation. Brazil, Luiz de Queiroz College of Agriculture, University of São Paulo. https://doi.org/10.11606/D.11.1999.tde-20220207-214730

Firouzi, S., Gholami Parashkoohi, M., Zamani, D. M., & Ranjber, I. (2022). An Investigation of the Environmental Impacts and Energy-Economic Analysis for Sugar Beet and Sugarcane Production Systems. *Sugar Tech*, *24*(6), 1851–1866. https://doi.org/10.1007/s12355-022-01135-1

Franco, H. C. J., Otto, R., Faroni, C. E., Vitti, A. C., Almeida de Oliveira, E. C., & Trivelin, P. C. O. (2011). Nitrogen in sugarcane derived from fertilizer under Brazilian field conditions. *Field Crops Research*, *121*(1), 29–41. https://doi.org/10.1016/j.fcr.2010.11.011

Gopalasundaram, P., Bhaskaran, A., & Rakkiyappan, P. (2012). Integrated Nutrient Management in Sugarcane. *Sugar Tech*, *14*(1), 3–20. https://doi.org/10.1007/s12355-011-0097-x

IBGE. (2025). Instituto Brasileiro de Geografia e Estatística. (Brazilian Institute of Geography and Statistics). *Produção agropecuária: Cana-de-açúcar*. https://www.ibge.gov.br/explica/producao-agropecuaria/cana-de-acucar/br/

Inman-Bamber, G. (2013). Sugarcane Yields and Yield-Limiting Processes. In *Sugarcane: Physiology, Biochemistry, and Functional Biology* (pp. 579–600). John Wiley & Sons, Ltd. https://doi.org/10.1002/9781118771280.ch21

IPEA. (2025). Instituto de Pesquisa Econômica Aplicada. (Institute for Applied Economic Research). *Ipeadata*. http://www.ipeadata.gov.br/Default.aspx

Keating, B. A., Robertson, M. J., Muchow, R. C., & Huth, N. I. (1999). Modelling sugarcane production systems I. Development and performance of the sugarcane module. *Field Crops Research*, *61*(3), 253–271. https://doi.org/10.1016/S0378-4290(98)00167-1

Lawes, R. A., Oliver, Y. M., & Huth, N. I. (2019). Optimal Nitrogen Rate Can Be Predicted Using Average Yield and Estimates of Soil Water and Leaf Nitrogen with Infield Experimentation. *Agronomy Journal*, *111*(3), 1155–1164. https://doi.org/10.2134/agronj2018.09.0607

Leo, S., De Antoni Migliorati, M., Nguyen, T. H., & Grace, P. R. (2023). Combining remote sensing-derived management zones and an auto-calibrated crop simulation model to determine optimal nitrogen fertilizer rates. *Agricultural Systems*, *205*, 103559. https://doi.org/10.1016/j.agsy.2022.103559

Maldaner, L. F., Molin, J. P., & Spekken, M. (2022). Methodology to filter out outliers in high spatial density data to improve maps reliability. *Scientia Agricola*, *79*(1), e20200178. https://doi.org/10.1590/1678-992X-2020-0178

Mantoam, E. J., Romanelli, T. L., & Gimenez, L. M. (2016). Energy demand and greenhouse gases emissions in the life cycle of tractors. *Biosystems Engineering*, *151*, 158–170. https://doi.org/10.1016/j.biosystemseng.2016.08.028

Meier, E. A., & Thorburn, P. J. (2016). Long Term Sugarcane Crop Residue Retention Offers Limited Potential to Reduce Nitrogen Fertilizer Rates in Australian Wet Tropical Environments.

Frontiers in Plant Science, *7, 1017*. https://doi.org/10.3389/fpls.2016.01017

Milan, M., & Rosa, J. H. M. (2015). Corte, transbordo e transporte (CTT): Aspectos relevantes e uso da modelagem para CTT. In *Processos agrícolas e mecanização da cana-de-açúcar*. Brazil, Luiz de Queiroz College of Agriculture, University of São Paulo.

Miranda, D. A. R., de Oliveira Alari, F., Oldoni, H., Bazzi, C. L., do Amaral, L. R., & Graziano Magalhães, P. S. (2021). Delineation of management zones in integrated crop–livestock systems. *Agronomy Journal*, *113*(6), 5271–5286. https://doi.org/10.1002/agj2.20912

Molin, J. P., Amaral, L. R., & Colaço, A. F. (2015). *Agricultura de precisão*. Brazil, Oficina de Textos.

Mulla, D. J. (2013). Twenty five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps. *Biosystems Engineering*, *114*(4), 358–371. https://doi.org/10.1016/j.biosystemseng.2012.08.009

Naseri, H., Parashkoohi, M. G., Ranjbar, I., & Zamani, D. M. (2021). Energy-economic and life cycle assessment of sugarcane production in different tillage systems. *Energy*, *217*, 119252. https://doi.org/10.1016/j.energy.2020.119252

Nawar, S., Corstanje, R., Halcro, G., Mulla, D., & Mouazen, A. M. (2017). Chapter Four - Delineation of Soil Management Zones for Variable-Rate Fertilization: A Review. In D. L. Sparks (Ed.), *Advances in Agronomy* (Vol. 143, pp. 175–245). Academic Press. https://doi.org/10.1016/bs.agron.2017.01.003

Nelson, D. W., & Sommers, L. E. (1996). Total Carbon, Organic Carbon, and Organic Matter. In *Methods of Soil Analysis* (pp. 961–1010). John Wiley & Sons, Ltd. https://doi.org/10.2136/sssabookser5.3.c34

Ottoni, M. V., Ottoni Filho, M. G., Schaap, M. L. R. C., Lopes-Assad, O. C., & Rotunno Filho, O. C. (2018). Hydrophysical database for Brazilian soils (HYBRAS) and pedotransfer functions for water retention. *Vadose Zone Journal, 17*, 170095. https://doi.org/10.2136/vzj2017.05.0095

Pellizzi, G. (1992). Use of energy and labour in Italian agriculture. *Journal of Agricultural Engineering Research*, *52*, 111–119. https://doi.org/10.1016/0021-8634(92)80054-V

Quaggio, J. A., Cantarella, H., van Raij, B., Otto, R., Penatti, C. P., Rossetto, R., Vitti, G. C., Korndorfer, G. H., Trivelin, P. C. O., Mellis, E. V., Franco, H. C. J., Gava, G. J. de C., Vitti, A. C., & Dias, F. L. (2022). Cana-de-açúcar. In H. Cantarella, J. A. Quaggio, D. Mattos Jr., R. M. Boaretto, & B. van Raij (Eds.), *Boletim 100: Recomendações de adubação e calagem para o Estado de São Paulo* (2nd ed., pp. 173–186). Campinas, Brazil: Instituto Agronômico.

Sanches, G. M., & Otto, R. (2022). A novel approach for determining nitrogen requirement based on a new agronomic principle—sugarcane as a crop model. *Plant and Soil*, *472*(1), 29–43. https://doi.org/10.1007/s11104-021-05263-7

Sanches, G. M., Graziano Magalhães, P. S., & Junqueira Franco, H. C. (2019). Site-specific assessment of spatial and temporal variability of sugarcane yield related to soil attributes. *Geoderma*, *334*, 90–98. https://doi.org/10.1016/j.geoderma.2018.07.051

Sanches, G. M., Magalhães, P. S. G., Kolln, O. T., Otto, R., Rodrigues, F., Cardoso, T. F., et al. (2021). Agronomic, economic, and environmental assessment of site-specific fertilizer management of Brazilian sugarcane fields. *Geoderma Regional*, *24*, e00360. https://doi.org/10.1016/j.geodrs.2021.e00360

Sattolo, T. M. S., Mariano, E., Boschiero, B. N., & Otto, R. (2017). Soil carbon and nitrogen dynamics as affected by land use change and successive nitrogen fertilization of sugarcane. *Agriculture, Ecosystems & Environment*, *247*, 63–74. https://doi.org/10.1016/j.agee.2017.06.005

Shimada, M., & Osawa, Y. (2012). ALOS-2 science program and high resolution SAR applications. In *Proc. SPIE* (Vol. 8528, p. 852812). https://doi.org/10.1117/12.979379

Sisti, C. P. J., dos Santos, H. P., Kohhann, R., Alves, B. J. R., Urquiaga, S., & Boddey, R. M.

(2004). Change in carbon and nitrogen stocks in soil under 13 years of conventional or zero tillage in southern Brazil. *Soil and Tillage Research*, *76*(1), 39–58. https://doi.org/10.1016/j.still.2003.08.007

Stackhouse Jr, P. W., Westberg, D., Hoell, J. M., Chandler, W. S., & Zhang, T. (2015). Prediction of worldwide energy resource (POWER): Agroclimatology methodology, Version 1.0. 2. *Washington, DC: The National Aeronautics and Space Administration*.

Stanford, G. (1973). Rationale for Optimum Nitrogen Fertilization in Corn Production. *Journal of Environmental Quality*, *2*(2), 159–166. https://doi.org/10.2134/jeq1973.00472425000200020001x

Sun, X., Miao, Q., Gu, Y., Yang, L., & Wang, P. (2025). Research on the Physiological Mechanisms of Nitrogen in Alleviating Plant Drought Tolerance. *Plants*, 14(18), 2928. https://doi.org/10.3390/plants14182928

Tanaka, T. S. T., Colaço, A. F., Mieno, T., & Riley, S. S. (2026). Advanced data analytics for on-farm experimentation: methods, challenges, and opportunities for modern agronomic decision making. *Plant Production Science*, *29*(2), 271–292. https://doi.org/10.1080/1343943X.2026.2664854

Thorburn, P. J., Biggs, J. S., Palmer, J., Meier, E. A., Verburg, K., & Skocaj, D. M. (2017). Prioritizing Crop Management to Increase Nitrogen Use Efficiency in Australian Sugarcane Crops. *Frontiers in Plant Science*, *8, 1504*. https://doi.org/10.3389/fpls.2017.01504

van Ittersum, M. K., & Rabbinge, R. (1997). Concepts in production ecology for analysis and quantification of agricultural input-output combinations. *Field Crops Research*, *52*(3), 197–208. https://doi.org/10.1016/S0378-4290(97)00037-3

Verburg, K., Pasley, H. R., Biggs, J. S., Vogeler, I., Wang, E., Mielenz, H., et al. (2025). Review of APSIM's soil nitrogen modelling capability for agricultural systems analyses. *Agricultural Systems*, *224*, 104213. https://doi.org/10.1016/j.agsy.2024.104213

Vitti, G. C., Otto, R., & Ferreira, L. R. de P. (2015). Nutrição e adubação da cana-de-açúcar: manejo nutricional da cultura da cana-de-açúcar. In *Processos agrícolas e mecanização da cana-de-açúcar*. Piracicaba, Brazil: Luiz de Queiroz College of Agriculture, University of São Paulo.

Wartenberg, D. (1985). Multivariate Spatial Correlation: A Method for Exploratory Geographical Analysis. *Geographical Analysis*, *17*(4), 263–283. https://doi.org/10.1111/j.1538-4632.1985.tb00849.x

Wiedenfeld, R. P. (2000). Water stress during different sugarcane growth periods on yield and response to N fertilization. *Agricultural Water Management*, *43*(2), 173–182. https://doi.org/10.1016/S0378-3774(99)00053-0

Yang, W., Li, Z., Wang, J., Wu, P., & Zhang, Y. (2013). Crop yield, nitrogen acquisition and sugarcane quality as affected by interspecific competition and nitrogen application. *Field Crops Research*, *146*, 44–50. https://doi.org/10.1016/j.fcr.2013.03.008

Zeng, X. P., Zhu, K., Lu, J. M., Jiang, Y., Yang, L. T., Xing, Y. X., & Li, Y. R. (2020). Long-Term Effects of Different Nitrogen Levels on Growth, Yield, and Quality in Sugarcane. *Agronomy*, *10*(3), 353. https://doi.org/10.3390/agronomy1003035