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Reducing nitrogen use under optimal irrigation and planting date can sustain sugarcane yield and gross margin under climate change

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A R T I C L E I N F O

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A B S T R A C T

Sugarcane is a vital economic crop in Australia, supporting both agricultural and regional economies. However, its heavy reliance on high nitrogen (N) inputs raises costs and results in considerable losses to the environment. While climate warming is projected to enhance sugarcane yield in subtropical New South Wales (NSW), it remains unclear whether this benefit, combined with adaptive management, can sustain yields under reduced N use in future climates. To address this, the APSIM-Sugarcane model, validated with high accuracy (R^2=0.82 for yield and 0.73 for gross margin), was driven by projections from 27 global climate models under two Shared Socio-economic Pathways (SSP2–4.5 and SSP5–8.5) to simulate yield responses to varying N rates, irrigation levels, and planting dates across the main production regions of Condong, Broadwater, and Harwood in northern coastal NSW. Results indicated that under future climates, yield and gross margin increased under current management practices, with further gains under optimal management (50 % PAWC irrigation and planting in September). The optimal strategy remained unchanged across N rates, but yield and gross margin declined with reduced inputs. The lowest feasible N rate under future climates sustaining current yield (101–127 t ha^{-1}) and gross margin (2147–3122 AU$ ha^{-1}) was 60 kg ha^{-1} (a 40 % reduction from the current N rate of 100 kg ha^{-1}). At this level, irrigation was the primary driver of yield and gross margin, followed by temperature and CO_2. This study highlights practical nitrogen reduction strategies sustaining sugarcane productivity, profitability, and environmental sustainability under future climates in Australia.

1. Introduction

Sugarcane (*Saccharum spp.*) is a globally important crop cultivated in tropical and subtropical regions, serving as a major source of sugar and bioenergy (Nadeem et al., 2022; Shanthi et al., 2023). The harvested stem can yield up to 150 t ha^{-1} under favorable conditions (FAOSTAT, 2023). These high yields depend heavily on nitrogen (N) fertilizer use, as N is typically the most limiting nutrient for growth and development (Boschiero et al., 2020; Zeng et al., 2020). Given its high economic return, many farmers apply nitrogen well above recommended rates to minimize the risk of yield penalties (Thorburn et al., 2003; Yang et al., 2024). For example, nitrogen application rates in China often exceed 600 kg ha^{-1} annually (Li and Yang, 2015; Robinson et al., 2011), while in India, rates typically range from 400 to 500 kg ha^{-1} (Yang et al., 2024), nearly double the official guidelines in both countries (Kostka et al., 2009). However, excessive N does not significantly increase yield

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and may result in the loss of nearly half of the applied N, leading to high fertilizer costs and serious environmental pollution (Kandulu et al., 2018; Signor et al., 2013; Takeda et al., 2021).

In Australia, sugarcane is a major export crop, ranking second in export value and generating nearly AU$2 billion in annual revenue (DAFF, 2024; SugarAustralia, 2025). It is predominantly grown along a 2100 km stretch of the eastern coastline from tropical Queensland to subtropical northern New South Wales (NSW) (USDA, 2023; Wei et al., 2022). This region forms one of the most N-intensive cropping systems in Australia (SRA, 2014). Historically, nitrogen application rates have exceeded crop uptake by approximately 100 kg N ha^{-1} (Thorburn and Wilkinson, 2013). Vallis et al. (1996) reported that up to 60 % of applied N could be lost from sugarcane fields, contributing significantly to pollution in coastal ecosystems and groundwater (Mitchell et al., 2009; Thorburn et al., 2011a). This is particularly concerning for the Great Barrier Reef, where N runoff has been linked to coral decline and crown-of-thorns starfish outbreaks (Eberhard et al., 2017; MacNeil et al., 2019). In response, the Australian government established increasingly stringent targets to reduce dissolved inorganic nitrogen by 50 % by 2009 and 60 % by 2025 (Reef Water Quality Improvement Plan, 2009, 2025). To meet these targets, sugarcane growers are encouraged to adopt improved management practices that reduce N losses while maintaining yield (Biggs et al., 2013; Drewry et al., 2008; Queensland Government, 2024). For example, Thorburn et al. (2011a) found that, under scheduled irrigation, N inputs in the Burdekin region could be reduced to 100 kg ha^{-1} without compromising yields, compared to the historical recommendation of 220 kg ha^{-1}. Therefore, a critical priority is to assess the potential for similar substantial reductions across other sugarcane regions to improve sustainability without compromising productivity.

Climate change presents both challenges and opportunities for sugarcane production and the optimization of management strategies. Annual mean temperatures across Australia are projected to increase by 1.3–4.4 °C by the end of the century under low- to high-emission scenarios (CSIRO, 2025). Such warming may enhance sugarcane growth, particularly in subtropical regions such as northern coastal New South Wales (Everingham et al., 2015; Yao et al., 2026). Projections of increased minimum temperatures are expected to alleviate temperature-related growth constraints and potentially improve productivity (Park et al., 2008), while future warming may contribute to plausible yield gains (Everingham et al., 2014). In addition, elevated atmospheric CO_2 concentrations may further enhance sugarcane productivity by improving the efficiency of nitrogen, light, and water use, resulting in greater biomass accumulation due to the CO_2 fertilization effect (De Souza et al., 2008). Everingham et al. (2014) demonstrated that elevated CO_2 can mitigate water stress and improve yields, and Singels et al. (2013) reported that the combined effects of warming and elevated CO_2 could increase Australian sugarcane yields by approximately 4 %. However, climate change is also expected to alter rainfall patterns and increase the frequency and intensity of extreme rainfall events (CSIRO, 2024), threatening the sustainability of yield increases. Given these uncertainties, it is essential to understand how climate change affects sugarcane production and to develop adaptive management strategies that balance productivity with environmental sustainability.

Process-based crop simulation models, which represent biophysical processes governing crop growth, soil water, and nutrient dynamics, are invaluable tools for analyzing the complex interactions between diverse environmental and agronomic management conditions (Junior et al., 2022; Marin and Jones, 2014). Well-established sugarcane models like APSIM-Sugarcane (Keating et al., 1999), QCANE (Liu and Bull, 2001), CANEGRO (Inman-Bamber et al., 1993), and SAMUCA (Marin and Jones, 2014) were widely applied to assess climate change impacts and evaluate adaptive strategies (Farooq and Gheewala, 2020; Guhan et al., 2024; Shanthi et al., 2023; Verma et al., 2023). Among these management strategies, irrigation scheduling, planting date adjustment, and N management were identified as effective approaches for managing the impacts of climate change (Linnenluecke et al., 2018; Linnenluecke et al., 2020; Misra et al., 2022; Nadeem et al., 2022; Verma et al., 2023). For example, CANEGRO-based studies suggested that tailored planting date adjustments could enhance climate resilience (Ahmad et al., 2016), while optimized irrigation might be increasingly critical to sustaining yields under warming scenarios (Jones et al., 2015). Using the same model, recent work further indicated that integrating adjustments in planting date, irrigation, and N management could effectively offset climate-induced yield reductions (Nadeem et al., 2022). Several studies also explored N-related environmental impacts under future climates using these crop simulation models. Leite et al. (2026) used the SAMUCA model to show that climate change could boost sugarcane yields but accordingly increase nitrous oxide emissions, while Biggs et al. (2013) applied the APSIM-Sugarcane model to demonstrate that optimized management systems could mitigate N losses in Australian sugarcane regions under projected climates. However, no study to date has assessed the feasibility of reducing N inputs to the lowest level by combining irrigation and planting date optimization that maintain both yield and gross margin under climate change in sugarcane systems.

In this study, we applied a well validated APSIM-Sugarcane model with climate projections from 27 CMIP6 global climate models (GCMs) to evaluate the response of sugarcane yield to nitrogen application variation combining irrigation and planting date under future climate scenarios. In this study, we used the validated APSIM-Sugarcane model, incorporating climate projections from 27 CMIP6 global climate models, to assess sugarcane yield responses to varying nitrogen rates in combination with irrigation and planting dates under future climate scenarios. The objectives were to: (1) assess the interactive effects of N rate, irrigation level, and planting date on sugarcane yield and gross margin; (2) determine the minimum N rate required to sustain yields under future conditions; (3) analyze the relative contributions of climate and management factors to changes in yield and gross margin. This study is expected to provide practical nitrogen reduction strategies for sugarcane growers in northern coastal NSW, supporting both productivity and environmental sustainability under a changing climate.

2. Materials and methods

2.1. Study area

Northern coastal New South Wales includes three major sugarcane production zones corresponding to the Condong, Harwood, and Broadwater mills (Fig. 1a). The region experiences a humid subtropical climate, marked by high summer rainfall and comparatively dry winters (Liu et al., 2021). Condong in the north experiences the highest mean annual temperature of 20.4 °C and receives 1638 mm of rainfall. Both temperature and rainfall decrease gradually toward the south. At Broadwater and Harwood, mean temperatures are lower, averaging 19.9 °C. Annual rainfall is 1627 mm at Broadwater and declines further to 1314 mm at Harwood, which is the driest site (Fig. 1b).

In northern NSW, sugarcane is primarily rainfed, supported by high annual rainfall along with shallow groundwater (Everingham et al., 2015; Topp et al., 2022). The recommended annual N application rates (N_{rate}) are typically 100 kg ha^{-1} for plant crops and 120 kg ha^{-1} for ratoon crops (SRA, 2022), with September being the main planting month (SunshineSugar, 2022). However, in practice, the planting window often aligns with the harvest season (June to November), as planting or ratoon emergence typically occurs soon after harvest (SunshineSugar, 2025). In this study, a standardized management strategy including rainfed conditions, a N_{rate} of 100 kg ha^{-1} for plants (120 kg ha^{-1} for ratoons), and planting on September 1 was adopted as the reference management practice (MP_{ref}) for the historical period (1981–2020). The corresponding yield and gross margin were defined as the reference yield (Y_{ref}) and gross margin (GM_{ref}), respectively.

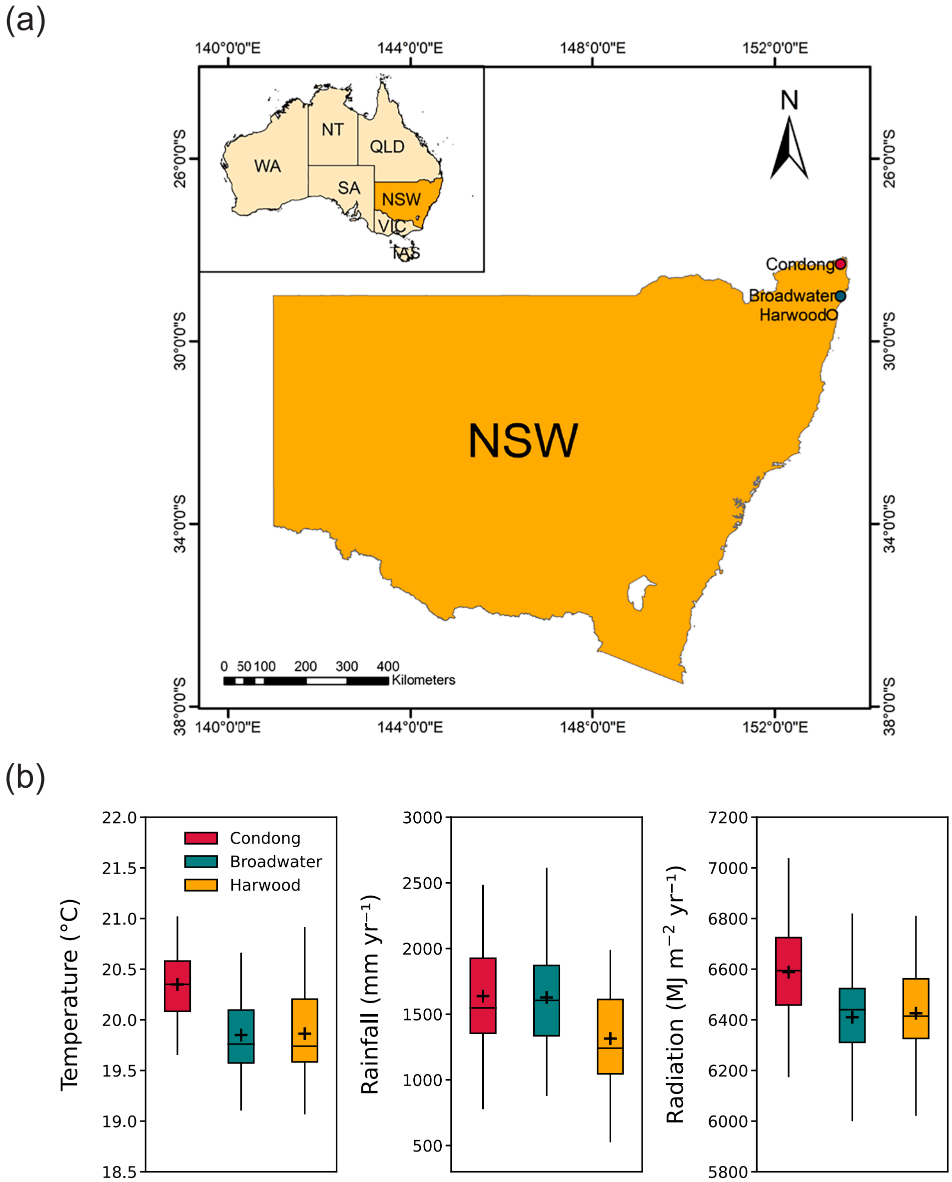

Fig. 1. (a) Locations of Condong, Broadwater, and Harwood in northern coastal NSW. (b) Mean annual temperature, total annual rainfall, and solar radiation for 1981–2020.

2.2. Climate and soil data

Historical daily climate data (temperature, rainfall and solar radiation) for the period 1980–2020 were downloaded from the Scientific Information for Land Owners (SILO) for three climate stations located in the Condong, Broadwater, and Harwood sugarcane-growing areas. Corresponding soil data were extracted from the Soil and Landscape Grid of Australia (SLGA) using the geographic coordinates of these stations. The extracted soil properties included bulk density, air dry water content, lower limit (LL15), saturated water content, soil texture, soil organic carbon, and pH.

CMIP6 incorporates a scientific framework that integrates Shared Socioeconomic Pathways (SSPs) and Representative Concentration Pathways (RCPs) to assess the combined impacts of socio-economic development and greenhouse gas emissions on future climate outcomes (Database, 2018). For this study, we used 27 CMIP6 GCMs (see Table S1 in Supplementary materials) under two representative scenarios: an intermediate "middle-of-the-road" pathway (SSP2–4.5) and a high-emission "fossil-fueled development" pathway (SSP5–8.5) (IPCC, 2021). To support site-level simulations, statistical downscaling was applied to each GCM for each site. This involved bias-correcting the simulated monthly climate data based on differences from observed data, followed by disaggregation into daily climate variables. This downscaling approach followed the methodology developed by Liu and Zuo (2012). Details of the annual atmospheric [CO_2] (ppm) calculation are given in the Supplementary materials.

2.3. Model description and simulations

2.3.1. The APSIM-Sugarcane model

The Agricultural Production Systems sIMulator (APSIM) is a deterministic, daily time-step modeling framework developed in Australia (McCown et al., 1996). APSIM-Sugarcane is the crop-specific module for simulating sugarcane growth and development (Keating et al., 1999) and has been widely validated and applied globally (Shanthi et al., 2023). It provides an integrated physiological framework for simulating plant and ratoon crops, incorporating phenology, canopy development, photosynthesis, biomass partitioning, sucrose accumulation, and water and nutrient uptake, as influenced by climate, soil, genotype, and management (Keating et al., 1999; O'Leary, 2000).

The APSIM-Sugarcane model simulates carbon fixation using an uncoupled radiation-use and transpiration efficiency (RUE and TE) on a daily time step (Monteith, 1988; Tanner and Sinclair, 1983), with assimilates partitioned into plant organs and sucrose in response to temperature, water, and nitrogen availability (Webster et al., 2009). Phenological development is driven by thermal time accumulation. Nitrogen demand is calculated as the product of maximum N concentration and biomass growth across plant components (Keating et al., 1999), with separate N pools for leaf, stalk, cabbage, and dead tissue (Marin et al., 2015). Nitrogen stress effects on growth, N translocation, and biomass accumulation are also incorporated (Marin et al., 2015; Zhao et al., 2017). Soil water dynamics follow a tipping-bucket approach (O'Leary, 2000). Water stress reduces leaf area expansion and RUE, and influences sucrose accumulation (Keating et al., 1999). The model's dynamic response to climate and environmental conditions enables flexible simulation of management practices, including fertilizer splitting, scheduled irrigation, plant–ratoon cycles, and variable planting and harvesting dates. This makes it well suited for evaluating climate–management interactions on sugarcane yield.

2.3.2. Model performance evaluation

In this study, we evaluated the performance of the APSIM-Sugarcane model by parameterizing and comparing the simulated historical yields (fresh weight) with reported yields (fresh weight) in northern coastal NSW (SunshineSugar, 2023). The data source is listed in Table S2 (Supplementary materials).

Three metrics were employed to assessing model accuracy and goodness of fit, including the coefficient of determination (R^2), root mean squared error (RMSE), and normalized root mean squared error (nRMSE) (Feng et al., 2022; Quan et al., 2024; Wu et al., 2025). A higher R^2 (closer to 1) and lower RMSE (closer to 0) indicate better model performance. The model is generally considered acceptable when nRMSE is below 20 % (Li et al., 2021). The equations for the evaluation metrics are as follows:

$$R^2 = 1 - \frac{SSR}{SST} \tag{1}$$

$$RMSE = \sqrt{\frac{1}{n}\sum\nolimits_{i=1}^{n}(P_i - O_i)^2} \tag{2}$$

$$nRMSE = \frac{RMSE}{\overline{O}} \times 100\% \tag{3}$$

where SSR is the sum of squared residuals; and SST is the total sum of squares; P_i is the predicted values; O_i is the observed values, and $\overline{O}$ is the mean of the observed values; n is the count of observations.

2.3.3. Modelling scenarios

Different N_{rate} levels were simulated in combination with varying irrigation levels and planting dates to assess their effects on sugarcane yield under climate change. In this study, four N_{rate} levels (40, 60, 80, and 100 kg ha^{-1}; Table 1) were selected to represent a gradient of reduced N application. Similarly, four irrigation levels ranging from rainfed to 70 % plant available water capacity (PAWC) (Table 1) were applied. This design was based on a sensitivity analysis of irrigation effects on sugarcane yield (see details in Supplementary materials), which evaluated irrigation levels from 0 % to 100 % PAWC in 10 % increments, indicating that yield gains plateaued beyond 70 % PAWC. Furthermore, to capture seasonal variability under climate change, six planting dates were scheduled monthly from 1 June to 1 November, aligning with the harvest season when planting or ratoon emergence typically follows harvest (SunshineSugar, 2025).

All scenarios were simulated using the APSIM-Sugarcane model for the baseline period (1981–2020) and two future periods: the mid-century (2040 s; 2021–2060) and the late-century (2080 s; 2061–2100) across the three sites in NSW. A typical cropping cycle of one plant crop and four ratoons was adopted, with each crop grown over 12 months (SunshineSugar, 2025). Model output was reported as fresh weight, consistent with industry standards for gross margin calculation (ABARES, 2022). Simulated outputs based on downscaled GCM projections were further bias-corrected using the approach of Yang et al. (2016), with additional details provided in the Supplementary materials.

The APSIM-Sugarcane model incorporated annual CO_2 concentration ([CO_2], ppm) for the period 1981–2100. The model accounts for elevated [CO_2] by modifying RUE and TE through multiplication with [CO_2] response factors (Marin et al., 2015; Park et al., 2008; Webster et al., 2009). Details of these factors and the variety parameters used in this study are provided in the Supplementary materials.

Table 1
Management practices used in this study. Bond font shows the reference management option.

Management practices	Management levels
Annual N input rate (N_{rate})	40 kg N ha^{-1}, 60 kg N ha^{-1}, 80 kg N ha^{-1}, **100 kg N ha^{-1}**
Irrigation	**No irrigation (Rain-fed)**, 30 % PAWC (30 %), 50 % PAWC (50 %), 70 % PAWC (70 %)
Planting date	1 June (Jun), 1 July (Jul), 1 August (Aug), **1 September (Sep)**, 1 October (Oct), 1 November (Nov), 1 December (Dec)

2.4. Gross margins

Long-term profitability of sugarcane systems was evaluated using gross margin (GM, AU$ ha^{-1} yr^{-1}), following the methods of SRA (2017) and Topp et al. (2022) :

$$GM = CI - AC - VC \tag{4}$$

where CI is cane income, derived from the product of on-farm price (AU$ t^{-1}) and yield (t ha^{-1}); AC includes agricultural management costs and levies (AU$ ha^{-1} or AU$ t^{-1}); and VC represents irrigation costs.

Nitrogen fertilizer was applied as elemental N (kg ha^{-1}) and converted to equivalent urea rates (46 % N content) for gross margin calculations (Queensland Government, 2024). On-farm prices and economic costs are listed in Table 2, with irrigation cost details in Table S4 (Supplementary materials).

2.5. The calculation of yield and gross margin change

Changes in future yield (ΔY_{future}, %) and gross margin (ΔGM_{future}, %) were then calculated relative to these benchmarks using Eq. (5)–(6):

$$\Delta Y_{future} \quad (\%) = \frac{(Y_{future} - Y_{ref})}{Y_{ref}} \times 100\% \tag{5}$$

$$\Delta GM_{future} \quad (\%) = \frac{(GM_{future} - GM_{ref})}{GM_{ref}} \times 100\% \tag{6}$$

where Y_{future} and GM_{future} represent the simulated sugarcane yield and gross margin, respectively, under different management combinations for the 2040 s and 2080 s in SSP245 and SSP585 scenarios.

2.6. Quantifying the impacts of climate and management on yield and gross margin

To assess future changes in sugarcane yield and gross margin, we applied multiple linear regression to quantify the influence of major climatic drivers and management practices across scenarios. The

Table 2
On-farm sugarcane price and agricultural management costs used for gross margin calculations. Data are from ABARES (2022), DAFF (2025), SunshineSugar (2022), Champness et al. (2023) and Thompson et al. (2024).

Category	Description	Unit	Price
Cane income (CI)	On-farm sugarcane price	AU$ t^{-1}	38
Averaged costs (AC)	Levy	AU$ t^{-1}	0.43
	Contrasts	AU$ ha^{-1}	611
	Urea	AU$ t^{-1}	760
	Repairs/maintenance	AU$ ha^{-1}	190
	Hired labour	AU$ ha^{-1}	27
	Fuel, oil and grease	AU$ ha^{-1}	138
	Crop chemicals	AU$ ha^{-1}	121
	Electricity	AU$ ha^{-1}	10
	Rates	AU$ ha^{-1}	73
	Handling/marketing	AU$ ha^{-1}	57
	Interest	AU$ ha^{-1}	22
	Insurance	AU$ ha^{-1}	59
	Land rent	AU$ ha^{-1}	34
	Administration	AU$ ha^{-1}	31
	Motor vehicles	AU$ ha^{-1}	14
	Other cash costs	AU$ ha^{-1}	70
Variable cost (VC)	Irrigation	AU$ ML^{-1}	21.7
	Irrigation labor[a]	AU$ ha^{-1} $application^{-1}$	15

[a] The average cost including irrigation labor use, vehicle use, and visit per irrigation event (Champness et al., 2023; Thompson et al., 2024).

analysis assessed the relationships between changes in projected optimal yield and gross margin under the lowest N_{rate} that sustained yield, and corresponding changes in climatic factors and management practices (see Eq. (12)). Climatic factors included changes in mean temperature (ΔT, °C), total rainfall (ΔRf, mm), global solar radiation (ΔRad, MJ m^{-2}), and atmospheric CO_2 concentration (ΔCO_2, ppm) during the growth period. The only management variable under the lowest N_{rate} was irrigation amount (ΔIrr, mm) at the optimal planting date. We formulated the regression model as:

$$\Delta Y_{opt\text{-}lowest\_Nrate} \text{ or } \Delta GM_{opt\text{-}lowest\_Nrate} = a \times \Delta T + b \times \Delta Rf + c \times \Delta CO_2 + d \times \Delta Rad + e \times \Delta Irr \quad (7)$$

where $\Delta Y_{opt\text{-}lowest\_Nrate}$ represents the projected yield change under the lowest N_{rate}, while $\Delta GM_{opt\text{-}lowest\_Nrate}$ indicates the corresponding change in gross margin. a, b, c, d, and e are the fitted coefficients.

The relative contribution of individual variables for explaining variation in yield and gross margin was assessed using partial coefficients of determination (partial R^2). It is defined as:

$$\text{Partial}R^2 = \frac{R^2_{full} - R^2_{reduced}}{1 - R^2_{reduced}} \quad (8)$$

where R^2_{full} is the coefficient of determination from the model with all variables, whereas $R^2_{reduced}$ comes from the model excluding the target variable.

Fig. 2 shows the overall framework and methodology employed in this study.

3. Results

3.1. Model performance evaluation

The APSIM-Sugarcane model demonstrated strong agreement with observations for both yield and gross margin. It explained 82 % of the variance in yield ($R^2 = 0.82$) and 73 % in gross margin ($R^2 = 0.73$), with RMSE values of 6.2 t ha^{-1} and 95 AU$ ha^{-1}, respectively (Fig. 3). Regression slopes of 0.97–0.98 further confirm the close correspondence between simulations and observations, while nRMSE values below 10 % highlight the model's robustness. These results supported the model as a reliable tool for simulating sugarcane production in northern coastal

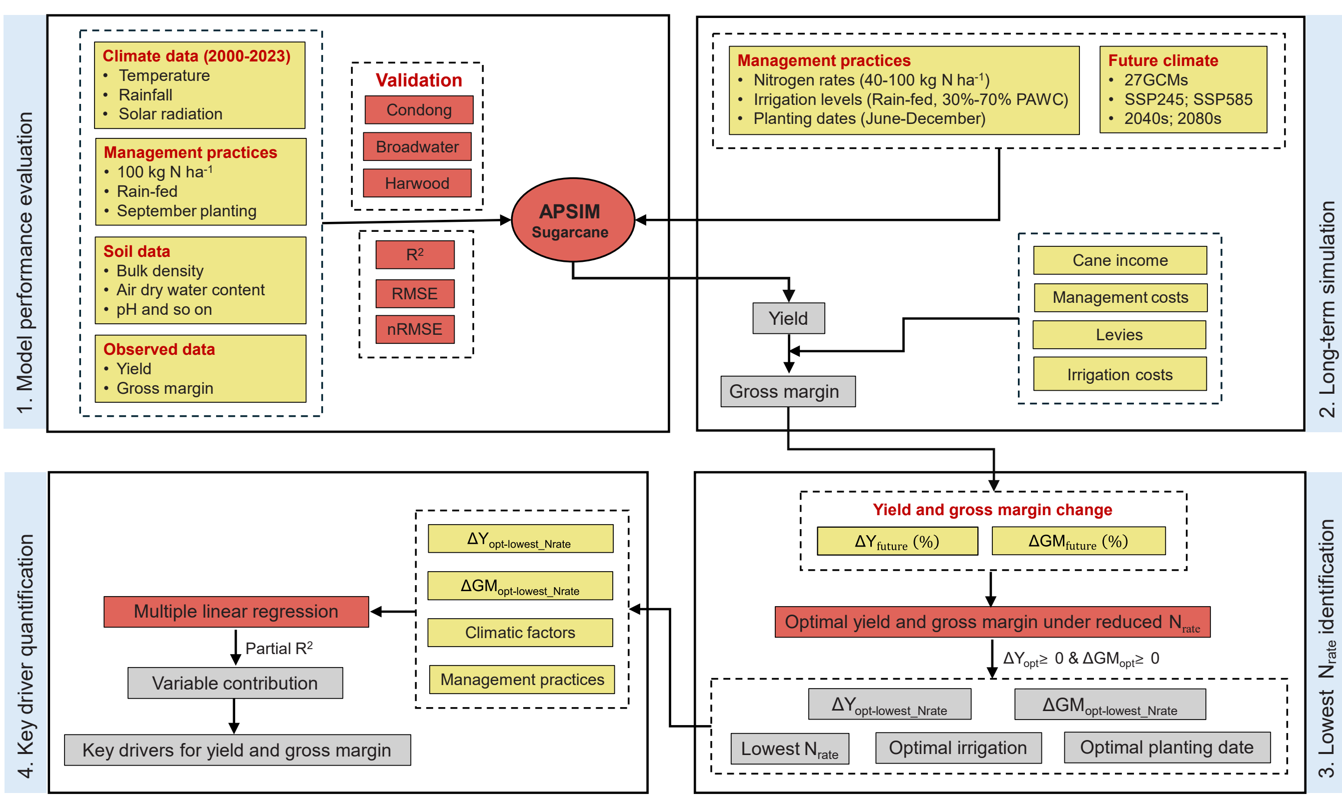

Fig. 2. Flow diagram of the methodology used in this study. APSIM, Agricultural Production Systems sIMulator; GCM, global climate model; SSP, shared socioeconomic pathways; ΔY_{future} (%), future yield changes; ΔGM_{future} (%), future gross margin changes; ΔY_{opt}, optimal yield; ΔGM_{opt}, optimal gross margins; N_{rate}, nitrogen rate; $\Delta Y_{opt\text{-}lowest\_Nrate}$, the projected yield change under the lowest N_{rate}; $\Delta GM_{opt\text{-}lowest\_Nrate}$, the projected gross margin change under the lowest N_{rate}.

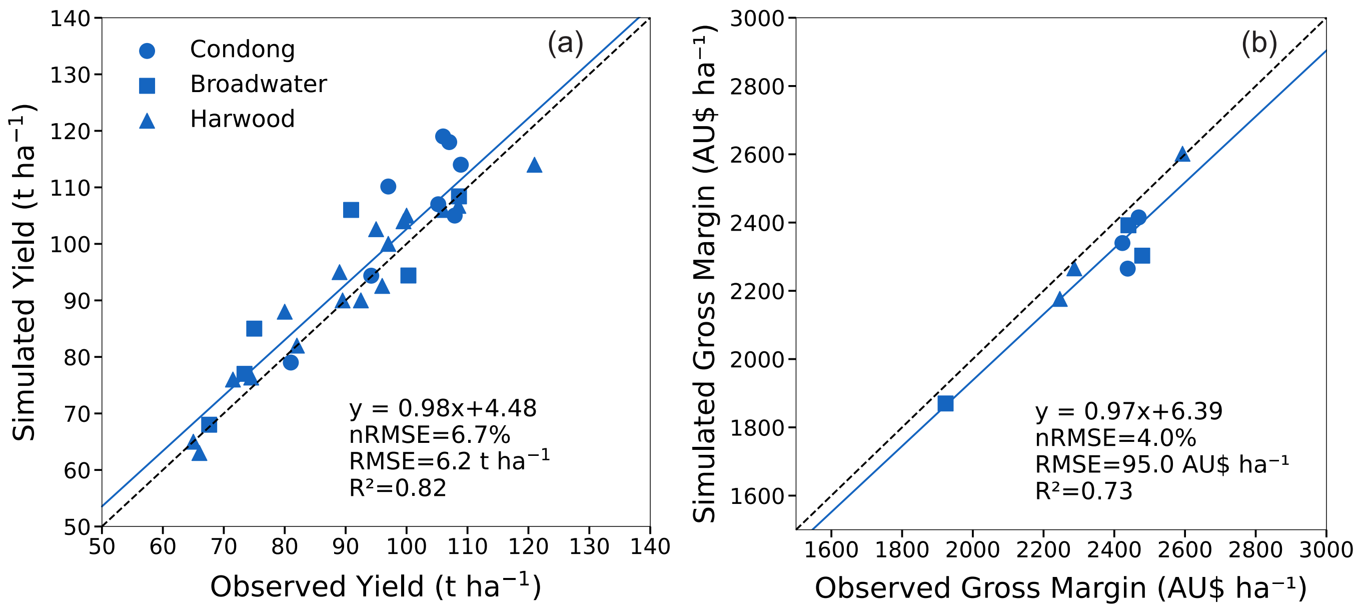

Fig. 3. Validation of APSIM-Sugarcane against observed yield and gross margin at Condong, Broadwater, and Harwood in NSW. Observed data were obtained from SunshineSugar (2023) and are detailed in Table S2 (Supplementary materials). The dashed lines represent the 1:1 ratio, and the blue lines indicate the linear regression fit.

NSW.

3.2. Projected future climate

Projected future climatic factors showed similar patterns among the three sites, with distinct differences observed between SSP245 and SSP585 (Fig. 4). Mean temperature is expected to rise relative to the baseline period, showing greater warming under SSP585 (Fig. 4a). By the 2080 s, SSP585 showed the largest projected temperature rise, with the multi-model ensemble estimating an average increase of up to 3.4 °C, while the smallest increase occurred under SSP245 in the 2040 s, at approximately 1.1 °C. Solar radiation was also projected to rise for both SSP245 and SSP585, with more notable changes in the 2080 s compared with the 2040 s (Fig. 4c). Under SSP245, the 2080 s recorded the largest increase, averaging 84 MJ m^{-2} (1.0 %) across the three sites.

In contrast, rainfall projections exhibited a slight decrease in future periods relative to the baseline (Fig. 4b), with average reductions of 13 mm (0.9 %) under SSP245 and 24 mm (1.5 %) under SSP585. However, rainfall changes varied substantially across the 27 GCMs, reflected in the broad 10th–90th percentile range. Some climate models projected increased rainfall, whereas others demonstrated declines, suggesting considerable uncertainty associated with future rainfall patterns. The largest spread occurred at Condong under SSP585 in the 2080 s, with changes ranging from −288 mm (−16.9 %) to + 285 mm (+16.6 %).

3.3. Projected sugarcane yield changes

Projected sugarcane yields increased by 7–13 % under SSP245 and 9–24 % under SSP585 from the 2040 s to the 2080 s compared to MP_{ref} (rainfed, planting on September 1, and 100 kg N ha^{-1} under historical climate) across the three sites (Fig. 5). However, varying planting dates and irrigation levels led to substantial differences in projected yield changes under both emission scenarios. Under rainfed conditions, delaying planting from June to September increased yields, peaking in September, beyond which a slight decline was observed. Irrigation further enhanced this positive response, with 50 % of PAWC identified as the most effective irrigation level. Beyond this threshold, additional irrigation resulted in minimal yield improvements (typically < 1 %).

For N_{rate} ranging from 100 to 40 kg ha^{-1}, the patterns in yield change remained consistent across both future periods and emission scenarios at all three sites. Across all N_{rate} levels, optimal yields (Y_{opt}) were achieved under 50 % PAWC irrigation combined with a September planting date. However, as N_{rate} decreased, yield gains declined correspondingly under both SSP245 and SSP585 across the three sites. For example, under SSP245, reducing the N_{rate} from 100 to 80 kg ha^{-1} led to a reduction in Y_{opt} increases from 16 % to 9 % in the 2040 s, and from 21 % to 14 % in the 2080 s, averaged across the three sites. When the N_{rate} was further reduced to 60 kg ha^{-1}, no yield increase was observed in the 2040 s, and only 4 % increase occurred in the 2080 s across the three sites. At the lowest input level of 40 kg ha^{-1}, Y_{opt} fell below baseline levels, with reductions of 10 % in the 2040 s and 6 % in the 2080 s. In contrast, yields were consistently higher under SSP585 across all managements. With an N_{rate} of 100 kg ha^{-1}, Y_{opt} increased by 18 % in the 2040 s and 29 % in the 2080 s across the three sites. When the N_{rate} was reduced to 80 kg ha^{-1}, Y_{opt} gains declined to 11 % in the 2040 s and 22 % in the 2080 s. At 60 kg ha^{-1}, Y_{opt} still increased by 4 % in the 2040 s and 14 % in the 2080 s. Notably, at the lowest N input of 40 kg ha^{-1}, Y_{opt} under SSP585 was 6 % lower than the baseline in the 2040 s but increased by 4 % in the 2080 s.

3.4. Projected changes in gross margin

Projected changes in gross margin followed patterns similar to those of yield across management combinations. Under MP_{base}, projected gross margins increased by 15–21 % from the 2040 s to the 2080 s under SSP245 across all study sites, and a larger increase of 18–37 % was observed under SSP585 (Fig. 6). For N_{rate} ranging from 100 to 40 kg ha^{-1}, varying planting dates and irrigation levels resulted in considerable variability in gross margin across the three sites under both future periods and emission scenarios. The optimal gross margins (GM_{opt}) at each N_{rate} were consistently achieved with 50 % PAWC irrigation combined with planting in September.

Under 100 kg N ha^{-1}, GM_{opt} increased by 27–34 % under SSP245 during the 2040 s to 2080 s. As N_{rate} decreased to 80 kg ha^{-1}, the magnitude of GM_{opt} improvement diminished to 15 % in the 2040 s and 22 % in the 2080 s. When the N_{rate} was further reduced to 60 kg ha^{-1}, GM_{opt} fell below baseline levels, with a reduction of 1 % in the 2040 s,

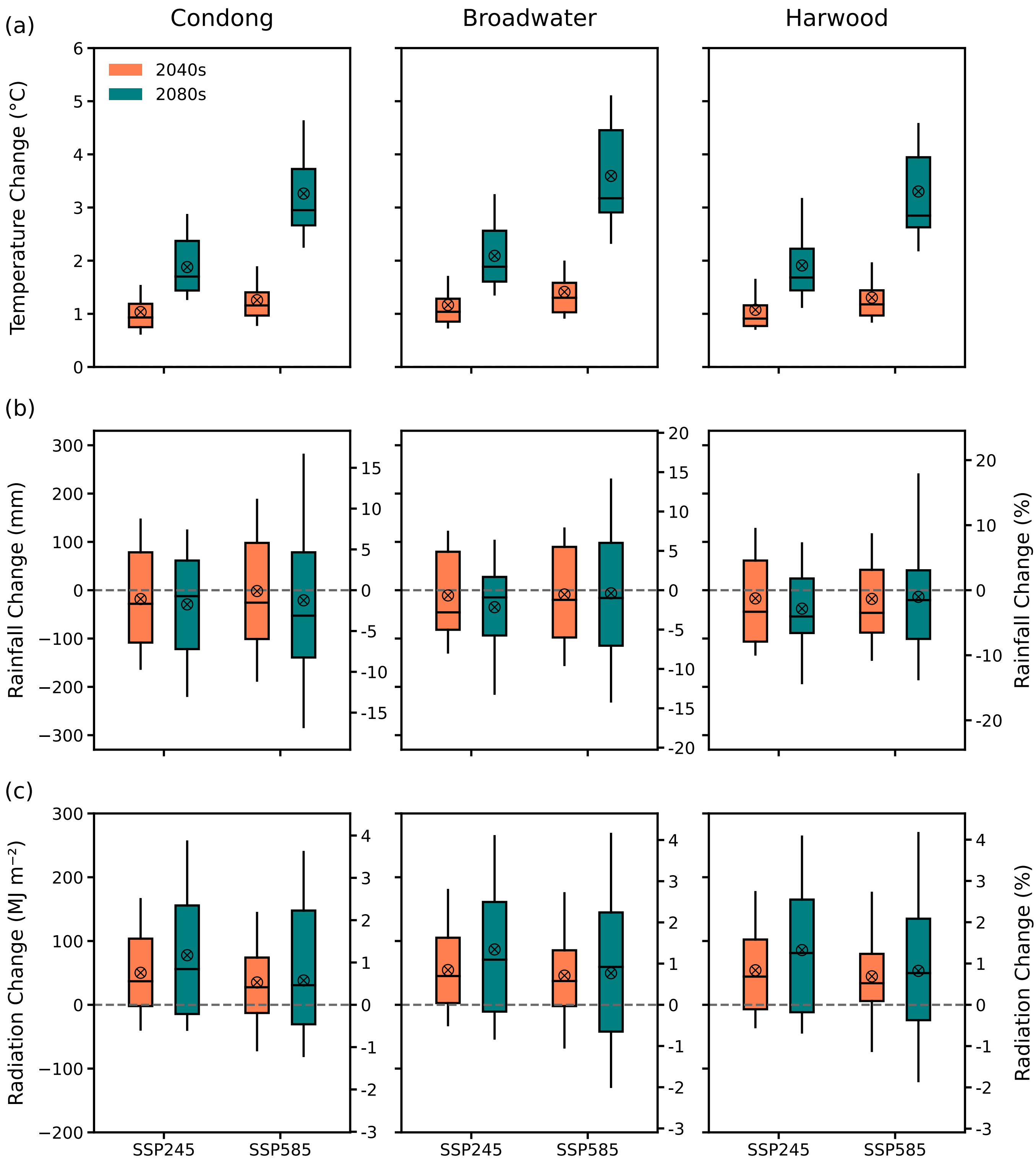

Fig. 4. Climate projections for the three study sites under SSP245 and SSP585 based on 27 GCMs. Panels show changes in (a) mean annual temperature, (b) rainfall, and (c) solar radiation, relative to the baseline (1981–2020) for two future periods: mid-century (2040 s; 2021–2060) and late-century (2080 s; 2061–2100). Boxes show the interquartile range from the 25th to 75th percentiles, whiskers represent the 10th–90th percentiles, the black line represents the median, and crosshairs indicate the mean.

and only 9 % increase occurred in the 2080 s across the three sites. At the lowest input level of 40 kg ha^{-1}, GM_{opt} decreased by 14 % in the 2040 s and by 7 % in the 2080 s. In contrast, GM_{opt} were consistently higher under SSP585 across all management combinations. With an N_{rate} of 100 kg ha^{-1}, GM_{opt} increased by 29 % in the 2040 s and 48 % in the 2080 s across the three sites. When the N_{rate} was reduced to 80 kg ha^{-1}, GM_{opt} gains declined to 18 % in the 2040 s and 37 % in the 2080 s. At 60 kg ha^{-1}, GM_{opt} still increased by 4 % in the 2040 s and 23 % in the 2080 s. Notably, at the lowest N_{rate} of 40 kg ha^{-1}, GM_{opt} under SSP585 was 11 % lower than the baseline in the 2040 s but increased by 7 % in the 2080 s.

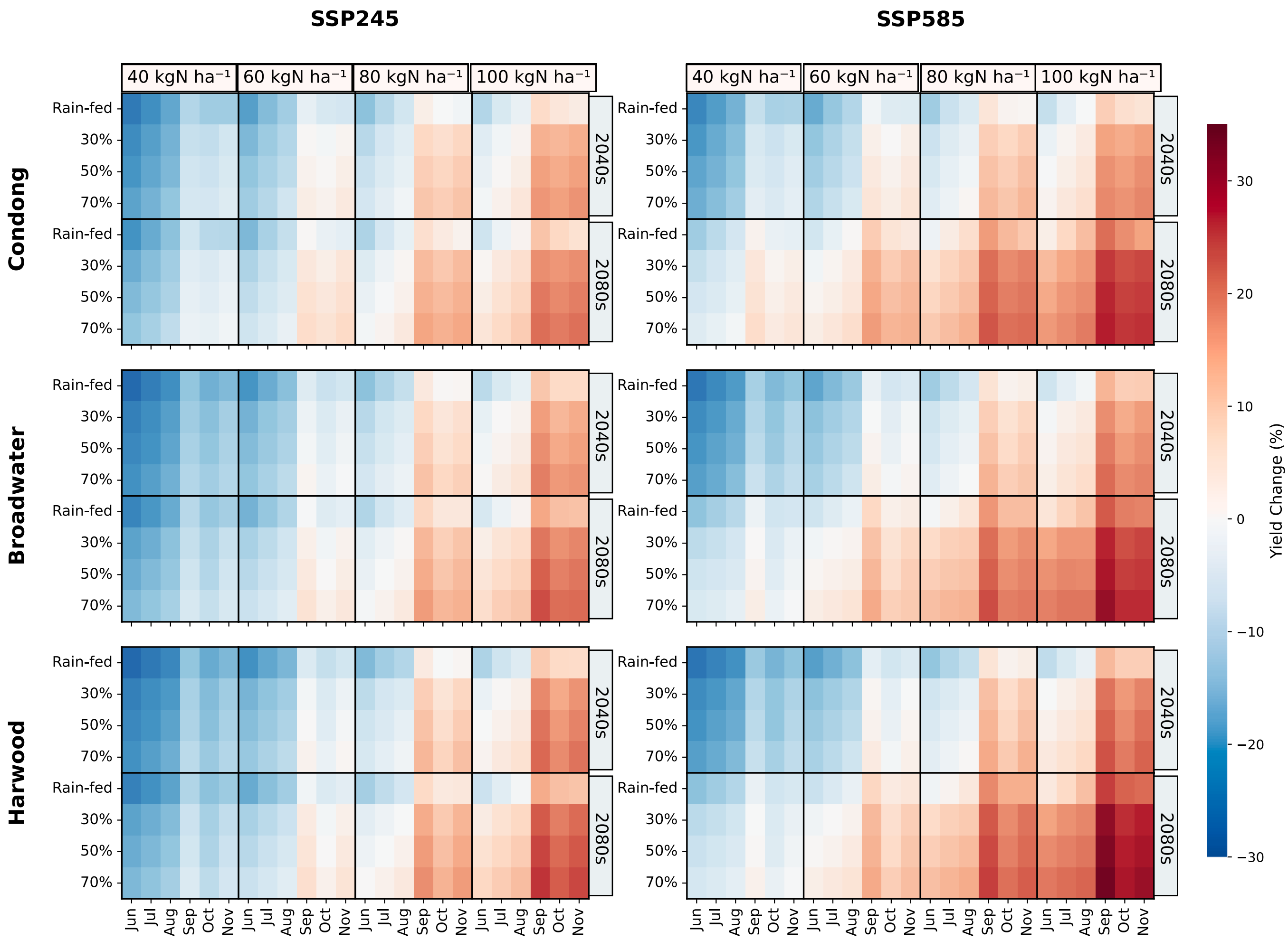

Fig. 5. Projected sugarcane yield responses to different irrigation levels and planting dates under four nitrogen rates (40, 60, 80, and 100 kg N ha^{-1}), simulated with 27 GCMs under SSP245 and SSP585 for the three study sites in NSW. Changes in projected yield are measured against the GM_{ref} under MP_{ref} (rainfed, planting on 1 September, and 100 kg N ha^{-1} with historical climate) for the mid-century (2040 s; 2021–2060) and the late-century (2080 s; 2061–2100).

3.5. Optimal yield and gross margin under reduced N rates

We used 50 % PWAC and planting on September 1 as the optimal management for each N_{rate} to identify the lowest N_{rate} that maintained both yield and gross margin under climate change. Across the three sites in NSW, projected Y_{opt} and GM_{opt} declined progressively with lower N_{rate} (80, 60, and 40 kg N ha^{-1}) across both future periods under SSP245 and SSP585 (Fig. 7). At 80 kg N ha^{-1}, all projected Y_{opt} and GM_{opt} exceeded the baseline, with Y_{opt} ranging from 112 to 126 t ha^{-1} under SSP245 and 113–35 t ha^{-1} under SSP585. Corresponding GM_{opt} ranged from 2486 AU$ ha^{-1} to 3036 AU$ ha^{-1} under SSP245 and from 2547 AU$ ha^{-1} to 3386 AU$ ha^{-1} under SSP585. At 60 kg N ha^{-1}, Y_{opt} declined but generally remained sufficient to meet or exceed baseline yields across all future periods and scenarios, except at Broadwater in the 2040 s under SSP245, where it was projected to fall slightly below the baseline by less than 1 t ha^{-1}, indicating comparable productivity. Under SSP245, projected yields ranged from 101 to 118 t ha^{-1} between the 2040 s and 2080 s, while under SSP585, yields ranged from 105 to 127 t ha^{-1}. The corresponding GM_{opt} values all met or exceeded baseline levels, ranging from 2147 to 2771 AU$ ha^{-1} under SSP245 and from 2205 to 3122 AU$ ha^{-1} under SSP585. In contrast, at the N_{rate} of 40 kg N ha^{-1}, only SSP585 in the 2080 s sustained both yield and gross margin above the baseline, with Y_{opt} of 118, 105, and 101 t ha^{-1} for Condong, Broadwater, and Harwood, respectively, and GM_{opt} of 2807, 2340, and 2200 AU$ ha^{-1}. All other combinations of periods and scenarios at this low N_{rate} were insufficient to maintain both yield and profitability. Therefore, among the reduced N_{rate} levels (80–40 kg N ha^{-1}), 60 kg N ha^{-1} was the lowest N_{rate} that generally sustained both yield and gross margin across future scenarios.

3.6. Quantifying the influences of climate and management on yield and gross margin

Multiple linear regression was employed to evaluate the effects of climate and management factors on sugarcane yield and gross margin at the lowest N_{rate} of 60 kg N ha^{-1} (Tables 3–4). The model explained 98–99 % of the variation in yield and 98 % in gross margin. Temperature, CO_2, solar radiation, and irrigation had statistically significant positive effects on both yield and gross margin across all sites ($p < 0.05$–0.001). Among these, ΔIrr accounted for the greatest variation, with partial R^2 values of 0.57–0.68 for yield and 0.47–0.56 for gross margin for all sites. In contrast, the second most influential factor differed by site. ΔT had a greater impact at Broadwater and Harwood, while ΔCO_2 showed a stronger influence at Condong. Solar radiation had comparatively lower explanatory power than the above three variables, though its influence was more pronounced at Condong.

These site-specific responses further highlight the variability in factor influence across locations. For example, Harwood was most sensitive to ΔT, with yield increasing by 3378 kg ha^{-1} °C^{-1} and gross margin by 126.02 AU$ ha^{-1} °C^{-1}. At Condong, changes in ΔCO_2 and ΔRad had the greatest impact, leading to yield gains of 2093 kg ha^{-1} per 100 ppm [CO_2] and 12.03 kg ha^{-1} per MJ m^{-2} of radiation. Corresponding gains

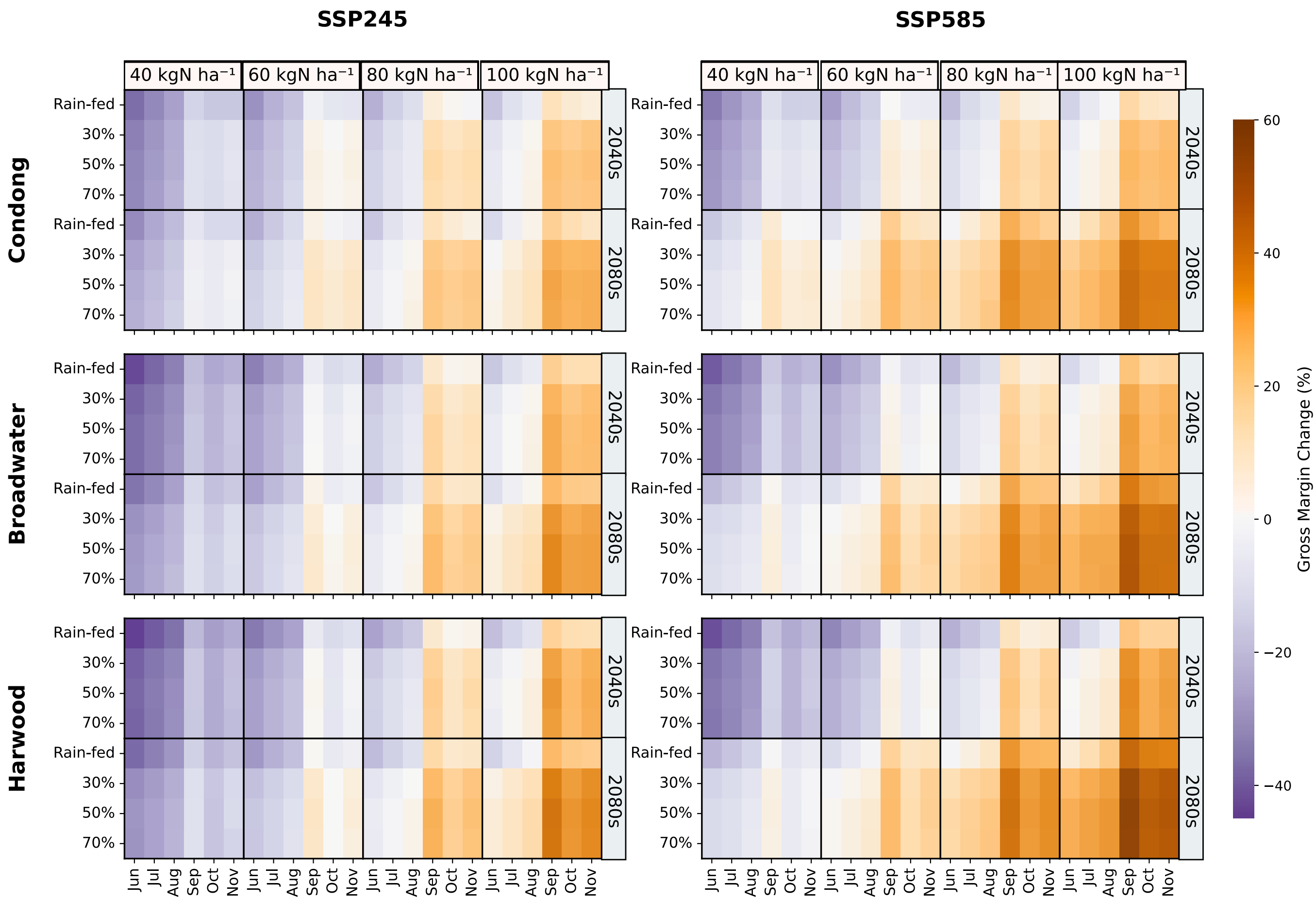

Fig. 6. Projected sugarcane gross margin responses to different irrigation levels and planting dates under four nitrogen rates (40, 60, 80, and 100 kg N ha^{-1}), simulated with 27 GCMs under SSP245 and SSP585 for the three study sites in NSW. Changes in projected gross margin are measured against the GM_{ref} under MP_{ref} (rainfed, planting on September 1, and 100 kg N ha^{-1} under historical climate) for the mid-century (2040 s; 2021–2060) and the late-century (2080 s; 2061–2100).

in gross margin were 78.03 AU$ ha^{-1} per 100 ppm [CO_2] and 0.45 AU$ ha^{-1} per MJ m^{-2} of radiation. In comparison, the influence of ΔIrr was more uniform across sites, contributing average increases of 82.19 kg ha^{-1} mm^{-1} in yield and 2.39 AU$ ha^{-1} mm^{-1} in gross margin.

4. Discussion

The projected patterns of future climate change, including rising temperatures and varied rainfall, were consistent with earlier Australian studies that incorporated both regional and global climate models (AdaptNSW, 2024; Everingham et al., 2015; Nishant et al., 2021). Under future climate scenarios, sugarcane yield and gross margin were projected to increase under current optimal management practices in NSW, with improvements of 7–24 % in yield and 15–37 % in gross margin (Figs. 5–6), indicating potential benefits of climate change for sugarcane production. The positive effects of climate change were in agreement with previous findings in Australia (Park et al., 2008; Sexton et al., 2014). For example, Everingham et al. (2015) projected yield increases of 5–6 % under both low and high emission scenarios in NSW, while Singels et al. (2014) indicated a 4 % increase in Ayr, although the yield improvement was limited by elevated maintenance respiration under higher temperatures. In this study, when optimized management practices were applied, further increases of 16–29 % in yield and 27–48 % in gross margin were observed under future climate conditions. These findings aligned with earlier work showing that optimized practices improve sugarcane's adaptive capacity and productivity in response to climate change. For example, Webster et al. (2009) found that best management practices, such as zero tillage, legume fallows, and no nitrogen applied to plant crops, led to higher gross margins than conventional practices across future scenarios in the Tully–Murray region of Australia. Therefore, the combined benefits of climate change and optimized management provided an opportunity to offset yield losses associated with nitrogen reduction.

To identify the lowest feasible nitrogen input without compromising yield, this study simulated sugarcane response to combinations of varying irrigation levels and planting dates. The results showed that increased irrigation had a pronounced effect on yield improvement, with 50 % PAWC representing the most optimal balance between water supply and crop demand under future climate conditions. Moderate irrigation at this level effectively mitigated water deficits associated with projected rainfall decline, particularly during the grand growth stage occurring in the drier season from June to November (Liu et al., 2021). This stage is characterized by full canopy development and rapid biomass accumulation, which demand substantial water and play a decisive role in determining final yield (Gascho, 1985; Nyati, 1996). Similar to yield, the highest gross margins were achieved with 50 % PAWC irrigation, indicating that additional water input beyond this level produced only marginal yield gains and negligible improvements in economic returns. In addition, planting date served as a critical factor affecting yield. Planting in spring (September to November) consistently produced higher yields than planting in winter (June to August) across different nitrogen input levels, with September remaining optimal under both baseline and future climates. This indicated that climate change was unlikely to shift the optimal planting window for sugarcane in NSW, as planting in September and the subsequent growth months provided favorable conditions for physiological development and maximized the

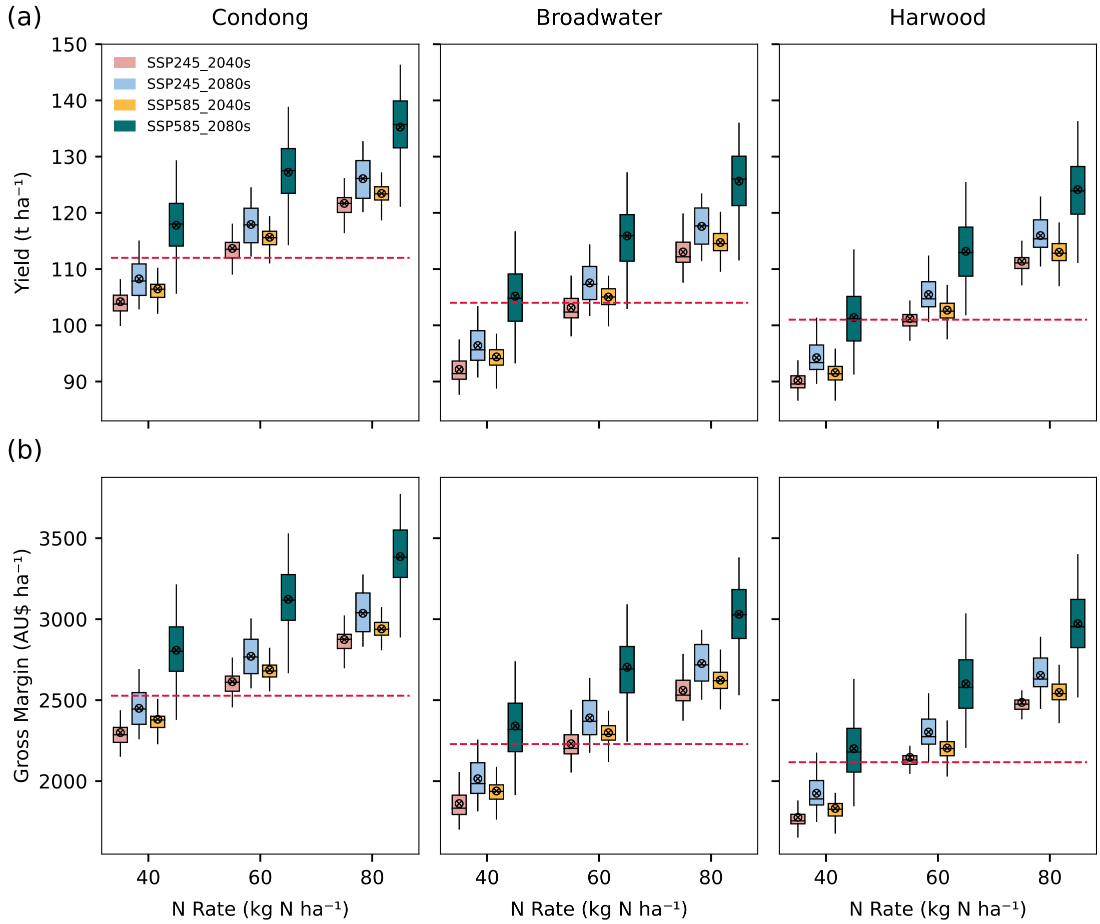

Fig. 7. Projected sugarcane yield (a) and gross margin (b) under planting in September and 50 % PAWC irrigation across reduced N application rates (40, 60, and 80 kg N ha^{-1}), simulated with 27 GCMs under SSP245 and SSP585 for the three study sites in NSW. Results are shown for the mid-century (2040 s; 2021–2060) and late-century (2080 s; 2061–2100). Red dashed lines denote the Y_{ref} and GM_{ref}. Boxes indicate the interquartile range (25th–75th percentiles), whiskers span the 10th–90th percentiles, black lines mark the median, and crosshairs the multi-model mean.

Table 3
Regression coefficients from the multiple linear regression model relating projected changes in optimal sugarcane yield at the lowest N_{rate} of 60 kg N ha^{-1} (ΔY_{opt-60}, kg ha^{-1}) to changes in temperature (ΔT, °C), rainfall (ΔRf, mm), solar radiation (ΔRad, MJ m^{-2}), CO_2 concentration (ΔCO_2, 100 ppm), and irrigation (ΔIrr, mm) across all sites. Significance levels are represented by * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$.

	Site	*a* (ΔT) (kg ha^{-1} °C^{-1})	*b* (ΔRf) (kg ha^{-1} mm^{-1})	*c* (ΔCO_2) (kg ha^{-1} 100 ppm^{-1})	*d* (ΔRad) (kg ha^{-1} (MJ $m^{-2})^{-1}$)	*e* (ΔIrr) (kg ha^{-1} mm^{-1})	R^2	Partial R^2				
								ΔT	ΔRf	ΔCO_2	ΔRad	ΔIrr
ΔY_{opt-60}	Condong	2692***	0.02	2093***	12.03***	73.71***	0.99	0.36	0.00	0.41	0.19	0.68
	Broadwater	2575***	4.02*	1569***	6.29*	92.38***	0.98	0.33	0.03	0.24	0.05	0.57
	Harwood	3378***	1.87	1336***	6.84*	80.48***	0.98	0.43	0.01	0.21	0.06	0.68

Table 4
Regression coefficients from the multiple linear regression model relating projected changes in optimal sugarcane gross margin at the lowest N_{rate} of 60 kg N ha^{-1} (ΔGM_{opt-60}, AU$ ha^{-1}) to changes in temperature (ΔT, °C), rainfall (ΔRf, mm), solar radiation (ΔRad, MJ m^{-2}), CO_2 concentration (ΔCO_2, 100 ppm), and irrigation (ΔIrr, mm) across all sites. Significance levels are represented by * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$.

	Site	*a* (ΔT) (AU$ ha^{-1} °C^{-1})	*b* (ΔRf) (AU $ ha^{-1} mm^{-1})	*c* (ΔCO_2) (AU $ ha^{-1} 100 ppm^{-1})	*d* (ΔRad) (AU $ ha^{-1} (MJ $m^{-2})^{-1}$)	*e* (ΔIrr) (AU $ ha^{-1} mm^{-1})	R^2	Partial R^2				
								ΔT	ΔRf	ΔCO_2	ΔRad	ΔIrr
ΔGM_{opt-60}	Condong	100.47***	0.00	78.03***	0.45***	2.09***	0.98	0.38	0.00	0.42	0.17	0.55
	Broadwater	96.06***	0.15*	58.49***	0.23*	2.77***	0.98	0.40	0.05	0.25	0.08	0.47
	Harwood	126.02***	0.07	49.78***	0.26*	2.32***	0.98	0.41	0.01	0.18	0.06	0.56

benefits of the future climate. In contrast, winter planting resulted in lower yields, as early-season low temperatures continued to limit emergence and delay canopy closure, reducing radiation interception and shortening the grand growth phase (Muchow et al., 1999).

As the N_{rate} decreased, sugarcane yield declined correspondingly. Since insufficient nitrogen limits chlorophyll and amino acid synthesis, thereby constraining photosynthetic activity and reducing the energy available for carbohydrate and structural biomass production (Macdonald et al., 1997). Nevertheless, under the optimized managements, N_{rate} could be reduced to as low as 40 kg N ha^{-1} (a 60 % reduction compared to reference) without compromising yield and gross margin in the future in NSW. This outcome reflected the synergistic benefits of adequate soil moisture and more favorable climate conditions, which enhanced nitrogen uptake efficiency and nutrient assimilation (Cerqueira et al., 2019; Wiedenfeld, 1995), thereby sustaining crop productivity even at lower fertilizer inputs. However, 40 kg N ha^{-1} was only achievable in the 2080 s under the high-emission scenario (SSP585), whereas a reduced rate of 60 kg N ha^{-1} was generally feasible across both future periods under the low-emission scenario (SSP245) and under the high-emission scenario in the 2040 s. The lower N requirement in the far future under SSP585 suggested that higher temperatures and enhanced CO_2 fertilization were likely to further promote sugarcane growth and partially offset N constraints. Notably, although reduced nitrogen applications could lower input costs, the realized economic benefits would depend on whether these savings, together with yield gains, were sufficient to offset the additional expenses associated with irrigation, thereby ensuring the long-term sustainability of gross margins.

Statistical analysis further showed that under 60 kg N ha^{-1}, increases in yield and gross margin were positively driven by future climatic factors and enhanced irrigation (Tables 3–4). Among these factors, irrigation contributed most strongly to variation in yield and gross margin, with partial R^2 values consistently highest for all sites. This highlighted irrigation as the primary factor influencing future yield increases. Under climate change, declining and more variable rainfall, together with rising temperatures projected to increase evapotranspiration, may elevate crop water demand and intensify water stress (Jones et al., 2015). Water stress restricts canopy development, photosynthesis, and nutrient uptake, ultimately limiting nitrogen use efficiency and biomass accumulation (Carr and Knox, 2011; Gonçalves et al., 2019; Inman-Bamber, 2004; Ma et al., 2021). Therefore, effective irrigation forms the foundation for supporting physiological processes and enables sugarcane to fully capitalize on favorable climate conditions.

Other than irrigation, among the climatic factors, ΔCO_2 was the most influential factor for yield and gross margin changes in Condong, while temperature had the greatest impact in Broadwater and Harwood (Tables 3–4). Such variation could be attributed to differences in local climate. At Condong, relatively high baseline temperatures reduce the limiting effect of additional warming, allowing CO_2 fertilization to play a more prominent role. Elevated [CO_2] improves sugarcane photosynthesis and water-use efficiency by allowing partial stomatal closure without reducing CO_2 uptake (Anwar et al., 2013; De Souza et al., 2008; Reddy and Hodges, 2000), leading to significant gains in biomass and yield (Biggs et al., 2013; Vu et al., 2006). It also increases photosynthetic nitrogen-use efficiency, suggesting greater potential for nitrogen reduction under high-emission scenarios (Anwar et al., 2013; Misra et al., 2019; Vu et al., 2006). However, the cooler baseline temperatures in Broadwater and Harwood made them more responsive to warming, which enhanced metabolic activity, growth rates, and radiation-use efficiency (Jones et al., 2015; Singels et al., 2013).

Several uncertainties and limitations of this study should be acknowledged. First, simulations assumed ideal conditions and did not account for biotic stresses (e.g., pests, diseases) or extreme weather events (e.g., heat or cold waves). These stress factors could reduce sugarcane growth and yield under future climates, potentially leading to overestimated productivity (Hussain et al., 2018; Pasley et al., 2023). Second, in evaluating climate change impacts on crop productivity, it is essential to account for management-induced uncertainties (Corbeels et al., 2018). The use of fixed monthly planting dates (i.e., the 1st day of each month) introduces a relatively coarse 30-day interval. This wider step may overlook potentially more optimal planting dates within each month, and thus, may slightly constrain the precision of estimating the truly optimal planting time. Additionally, we evaluated different combinations of irrigation levels and planting dates to identify optimal practices and assess the feasibility of nitrogen reduction. However, additional management options such as fallow legumes, reduced tillage, mill mud application, and trash blanket retention could further lower nitrogen needs and losses (Biggs et al., 2013; Drewry et al., 2008; SRA, 2008; Thorburn et al., 2011b). Future research should incorporate a broader range of management strategies to explore additional opportunities for minimizing nitrogen use while supporting sustainable sugarcane production.

5. Conclusion

This study evaluated the interactive effects of N rate, irrigation level, and planting date on sugarcane yield and gross margin under climate change in northern coastal NSW. Across different N rates, the optimal yield was consistently achieved with 50 % PAWC irrigation and planting in September, but declined progressively as N use decreased under SSP245 and SSP585 across the three sites. Under climate change, a 40 % reduction in N rate compared to the reference was identified as the minimum level at which both yield and gross margin could still be sustained. Among all factors, irrigation had the greatest influence on yield and gross margin, followed by climatic variables, all of which positively affected sugarcane yield. These findings provide critical insights on practical nitrogen reduction strategies that take advantage of the potential benefits of climate change to support long-term sugarcane productivity and environmental sustainability in Australia.

While this study identified the feasibility of the lowest N rate under future climate scenarios, the findings should be interpreted with caution, as they were derived under idealized conditions free of additional stress factors and with a limited set of management strategies. Future research should integrate realistic biotic/abiotic stressors and a more comprehensive suite of agronomic practices for building more resilient and low-input sugarcane production systems.

CRediT authorship contribution statement

Shijin Yao: Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Conceptualization. **Bin Wang:** Writing – review & editing, Supervision, Methodology, Conceptualization. **De Li Liu:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Fangzheng Chen:** Software. **Siyi Li:** Writing – review & editing, Software. **Keyu Xiang:** Writing – review & editing, Software. **Jianqiang He:** Writing – review & editing. **Mingxia Huang:** Software. **Meichen Feng:** Writing – review & editing. **Qiang Yu:** Writing – review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.agwat.2026.110160.

Data availability

Data will be made available on request.

References

ABARES, 2022. Financ. Perform. Sugarcane Farms 202021 to 2021–2022. ⟨https://www.agriculture.gov.au/abares/research-topics/surveys/sugar⟩.
AdaptNSW, 2024. Clim. Change NSW. ⟨https://www.climatechange.environment.nsw.gov.au/my-region/nsw⟩.
Ahmad, S., Nadeem, M., Abbas, G., Fatima, Z., Khan, R.J.Z., Ahmed, M., Ahmad, A., Rasul, G., Khan, M.A., 2016. Quantification of the effects of climate warming and crop management on sugarcane phenology. Clim. Res. 71, 47–61.
Anwar, M.R., Liu, D.L., Macadam, I., Kelly, G., 2013. Adapting agriculture to climate change: a review. Theor. Appl. Climatol. 113, 225–245.
Biggs, J., Thorburn, P., Crimp, S., Masters, B., Attard, S., 2013. Interactions between climate change and sugarcane management systems for improving water quality leaving farms in the Mackay Whitsunday region, Australia. Agric. Ecosyst. Environ. 180, 79–89.
Boschiero, B.N., Mariano, E., Torres-Dorante, L.O., Sattolo, T.M., Otto, R., Garcia, P.L., Dias, C.T., Trivelin, P.C., 2020. Nitrogen fertilizer effects on sugarcane growth, nutritional status, and productivity in tropical acid soils. Nutr. Cycl. Agroecosyst. 117, 367–382.
Carr, M., Knox, J.W., 2011. The water relations and irrigation requirements of sugar cane (Saccharum officinarum): a review. Exp. Agric. 47, 1–25.
Cerqueira, G., Santos, M., Marchiori, P., Silveira, N., Machado, E., Ribeiro, R., 2019. Leaf nitrogen supply improves sugarcane photosynthesis under low temperature. Photosynthetica 57, 18–26.
Champness, M., Vial, L., Ballester, C., Hornbuckle, J., 2023. Evaluating the performance and opportunity cost of a smart-sensed automated irrigation system for water-saving rice cultivation in temperate Australia. Agriculture 13, 903.
Corbeels, M., Berre, D., Rusinamhodzi, L., Lopez-Ridaura, S., 2018. Can we use crop modelling for identifying climate change adaptation options? Agric. For. Meteorol. 256 46–52.
CSIRO, 2024. Explor. Chang. Aust. 's. Clim. Is. Proj. Exp. Coming Decades Incl. Clim. Extrem. State Clim. 2024. ⟨https://www.csiro.au/en/research/environmental-impacts/climate-change/state-of-the-climate/future-climate⟩.
CSIRO, 2025. Clim. Proj. Aust. ⟨https://www.csiro.au/en/research/environmental-impacts/climate-change/Climate-change-information⟩.
DAFF, 2024. Agric. Commod. Rep. March 2024. ⟨https://www.agriculture.gov.au/abares/research-topics/agricultural-outlook/march-2024⟩.
DAFF, 2025. Levy Charg. rates. ⟨https://www.agriculture.gov.au/agriculture-land/farm-food-drought/levies/rates⟩.
Database, S., 2018. SSP Database (Shared Socioeconomic Pathways)-Version 2.0. https://tntcat.iiasa.ac.at/SspDb/dsd?Action=htmlpage&page=about.
De Souza, A.P., Gaspar, M., Da Silva, E.A., Ulian, E.C., Waclawovsky, A.J., Nishiyama Jr, M.Y., Dos Santos, R.V., Teixeira, M.M., Souza, G.M., Buckeridge, M.S., 2008. Elevated CO_2 increases photosynthesis, biomass and productivity, and modifies gene expression in sugarcane. Plant Cell Environ. 31, 1116–1127.
Drewry, J., Higham, W., Mitchell, C., 2008. Water quality improvement plan: Final report for Mackay Whitsunday region. Mackay Whitsunday Natural Resource Management Group.
Eberhard, R., Brodie, J., Waterhouse, J., 2017. Managing water quality for the Great Barrier Reef. Decis. Mak. Water Resour. Policy Manag. 265–289.
Everingham, Y., Inman-Bamber, G., Sexton, J., Stokes, C., 2015. A dual ensemble agroclimate modelling procedure to assess climate change impacts on sugarcane production in Australia. Agric. Sci. 06, 870–888.
Everingham, Y., Sexton, J., Inman-bamber, G., Stokes, C., 2014. Simulating Sugarcane Yield Response to Increased CO_2 Concentrations.
FAOSTAT, 2023. Food Agric. DataCrops Livest. Prod. ⟨https://www.fao.org/faostat/en/#data/QCL⟩.
Farooq, N., Gheewala, S.H., 2020. Assessing the impact of climate change on sugarcane and adaptation actions in Pakistan. Acta Geophys. 68, 1489–1503.
Feng, P., Wang, B., Harrison, M.T., Wang, J., Liu, K., Huang, M., Liu, D.L., Yu, Q., Hu, K., 2022. Soil properties resulting in superior maize yields upon climate warming. Agron. Sustain. Dev. 42, 85.
Gascho, G.J., 1985. Water-sugarcane relationships. Sugar J. 48 (6), 11–17.
Gonçalves, I., Barbosa, E., Santos, L., Nazario, A., Feitosa, D., Tuta, N., Matsura, E., 2019. Nutritional balance and production of sugarcane irrigated with treated wastewater through subsurface drip. Irrig. Sci. 37, 207–217.
Guhan, V., Annadurai, K., Easwaran, S., Marimuthu, M., Balu, D., Vigneswaran, S., Navinkumar, C., 2024. Assessing the impact of climate change on water requirement and yield of sugarcane over different agro-climatic zones of Tamil Nadu. Sci. Rep. 14, 8239.
Hussain, S., Khaliq, A., Mehmood, U., Qadir, T., Saqib, M., Iqbal, M.A., Hussain, S., 2018. Sugarcane production under changing climate: effects of environmental vulnerabilities on sugarcane diseases, insects and weeds. Clim. Change Agric. 1–17.
Inman-Bamber, N., 2004. Sugarcane water stress criteria for irrigation and drying off. Field Crops Res. 89, 107–122.
Inman-Bamber, N., Culverwell, T., McGlinchey, M., 1993. Predicting yield responses to irrigation of sugarcane from a growth model and field records. Proceedings of The South African Sugar Technologists' Association. Citeseer, pp. 66–72.
IPCC, 2021. Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. ⟨https://www.ipcc.ch/report/ar6/wg1/⟩.
Jones, M.R., Singels, A., Ruane, A.C., 2015. Simulated impacts of climate change on water use and yield of irrigated sugarcane in South Africa. Agric. Syst. 139, 260–270.
Junior, I.M.F., dos Santos Vianna, M., Marin, F.R., 2022. Assimilating leaf area index data into a sugarcane process-based crop model for improving yield estimation. Eur. J. Agron. 136, 126501.
Kandulu, J., Thorburn, P., Biggs, J., Verburg, K., 2018. Estimating economic and environmental trade-offs of managing nitrogen in Australian sugarcane systems taking agronomic risk into account. J. Environ. Manag. 223, 264–274.
Keating, B., Robertson, M., Muchow, R., Huth, N., 1999. Modelling sugarcane production systems I. Development and performance of the sugarcane module. Field Crops Res. 61, 253–271.
Kostka, G., Polzin, C., Scharrer, J., 2009. The future of sugar cane in (the) People's Republic of China and India–Supply constraints and expansion potential. Appl. Energy 86, S100–S107.
Leite, E.A., da Silva, E.H.F.M., Júnior, I.M.F., Marin, F.R., 2026. Assessing climate change impacts on sugarcane yield, crop water productivity, and nitrous oxide emissions across Brazil's bioenergy using the CSM-SAMUCA-sugarcane model. Agric. Syst. 231, 104494.
Li, L., Wang, B., Feng, P., Wang, H., He, Q., Wang, Y., Liu, D.L., Li, Y., He, J., Feng, H., 2021. Crop yield forecasting and associated optimum lead time analysis based on multi-source environmental data across China. Agric. For. Meteorol. 308, 108558.
Li, Y.-R., Yang, L.-T., 2015. Sugarcane agriculture and sugar industry in China. Sugar Tech. 17, 1–8.
Linnenluecke, M.K., Nucifora, N., Thompson, N., 2018. Implications of climate change for the sugarcane industry. WIREs Clim. Change 9, e498.
Linnenluecke, M.K., Zhou, C., Smith, T., Thompson, N., Nucifora, N., 2020. The impact of climate change on the Australian sugarcane industry. J. Clean. Prod. 246, 118974.
Liu, D.L., Bull, T.A., 2001. Simulation of biomass and sugar accumulation in sugarcane using a process-based model. Ecol. Model. 144, 181–211.
Liu, D.L., Teng, J., Ji, F., Anwar, M.R., Feng, P., Wang, B., Li, L., Waters, C., 2021. Characterizing spatiotemporal rainfall changes in 1960-2019 for continental Australia. Int. J. Climatol. 41, E2420–E2444.
Liu, D.L., Zuo, H., 2012. Statistical downscaling of daily climate variables for climate change impact assessment over New South Wales, Australia. Clim. Change 115, 629–666.
Ma, Z., Wu, W., Alatalo, J.M., Fu, W., Bai, Y., 2021. Optimal water-fertilizer combinations for efficient nitrogen fixation by sugarcane at different stages of growth. Water 13, 2895.
Macdonald, A., Poulton, P., Powlson, D., Jenkinson, D., 1997. Effects of season, soil type and cropping on recoveries, residues and losses of 15N-labelled fertilizer applied to arable crops in spring. J. Agric. Sci. 129, 125–154.
MacNeil, M.A., Mellin, C., Matthews, S., Wolff, N.H., McClanahan, T.R., Devlin, M., Drovandi, C., Mengersen, K., Graham, N.A., 2019. Water quality mediates resilience on the Great Barrier Reef. Nat. Ecol. Evol. 3, 620–627.
Marin, F.R., Jones, J.W., 2014. Process-based simple model for simulating sugarcane growth and production. Sci. Agric. 71, 1–16.
Marin, F.R., Thorburn, P.J., Nassif, D.S., Costa, L.G., 2015. Sugarcane model intercomparison: Structural differences and uncertainties under current and potential future climates. Environ. Model. Softw. 72, 372–386.
McCown, R.L., Hammer, G.L., Hargreaves, J.N.G., Holzworth, D.P., Freebairn, D.M., 1996. APSIM: a novel software system for model development, model testing and simulation in agricultural systems research. Agric. Syst. 50, 255–271.
Misra, V., Shrivastava, A., Mall, A., Solomon, S., Singh, A.K., Ansari, M.I., 2019. Can sugarcane cope with increasing atmospheric CO_2 concentration? Aust. J. Crop Sci. 13 780–784.
Misra, V., Solomon, S., Mall, A., Abid, M., Abid Ali Khan, M., Ansari, M.I., 2022. Drought stress and sustainable sugarcane production. In: Microbial biotechnology for sustainable agriculture, 1. Springer, pp. 353–368.
Mitchell, A., Reghenzani, J., Faithful, J., Furnas, M., Brodie, J., 2009. Relationships between land use and nutrient concentrations in streams draining a 'wet-tropics' catchment in northern Australia. Mar. Freshw. Res. 60, 1097–1108.
Monteith, J., 1988. Does transpiration limit the growth of vegetation or vice versa? J. Hydrol. 100, 57–68.
Muchow, R., Hughes, R., Horan, H., 1999. Evaluating the potential for improved sugar yields by assessing the climatic and soil constraints to production in southern cane-growing districts. SRDC Rep. Sched. 27, CTA012.
Nadeem, M., Nazer Khan, M., Abbas, G., Fatima, Z., Iqbal, P., Ahmed, M., Ali Raza, M., Rehman, A., Ul Haq, E., Hayat, A., 2022. Application of CSM-CANEGRO model for climate change impact assessment and adaptation for sugarcane in semi-arid environment of southern Punjab, Pakistan. Int. J. Plant Prod. 16, 443–466.
Nishant, N., Evans, J.P., Di Virgilio, G., Downes, S.M., Ji, F., Cheung, K.K., Tam, E., Miller, J., Beyer, K., Riley, M.L., 2021. Introducing NARCliM1.5: evaluating the performance of regional climate projections for southeast Australia for 1950–2100. Earth's. Future 9, e2020EF001833.
Nyati, C.T., 1996. Effect of irrigation regime on cane and sugar yields of variety NCo376 in the south-east lowveld of Zimbabwe. Proc. South Afr. Sugar Technol. Assn 70, 59–62.
O'Leary, G.J., 2000. A review of three sugarcane simulation models with respect to their prediction of sucrose yield. Field Crops Res. 68, 97–111.
Park, S., Creighton, C., Howden, M., 2008. Impact of climate change on the Australian sugar industry and adaptation options. Sugar Research and Development Corporation, Brisbane, Australia.

Pasley, H., Brown, H., Holzworth, D., Whish, J., Bell, L., Huth, N., 2023. How to build a crop model. A review. Agron. Sustain. Dev. 43, 2.
Quan, H., Wang, B., Wu, L., Feng, H., Wu, L., Wu, L., Li Liu, D., Siddique, K.H., 2024. Impact of plastic mulching and residue return on maize yield and soil organic carbon storage in irrigated dryland areas under climate change. Agric. Ecosyst. Environ. 362, 108838.
Queensland Government, 2024. Econ. Eval. Sugarcane Manag. Pract. that Improv. Water Qual. Tech. Rep. ⟨https://www.publications.qld.gov.au/dataset/05fe1bbd-1933-4205-851b-a469f915327e/resource/dd1cea62-4c09-43be-a7bb-112dc178a995/download/economics-of-improved-management-practices-for-sugarcane.pdf⟩.
Reddy, K.R., Hodges, H.F., 2000. Climate change and global crop productivity. CABI, Wallingford, UK.
Reef Water Quality Improvement Plan, 2009. Reef. Water Qual. Improv. Plan 2009. ⟨https://elibrary.gbrmpa.gov.au/jspui/bitstream/11017/1125/1/reef-plan-2009.pdf⟩.
Reef Water Quality Improvement Plan, 2025. Reef. 2050 Water Qual. Improv. Plan 20172022. ⟨https://www.reefplan.qld.gov.au/__data/assets/pdf_file/0017/46115/reef-2050-water-quality-improvement-plan-2017-22.pdf⟩.
Robinson, N., Brackin, R., Vinall, K., Soper, F., Holst, J., Gamage, H., Paungfoo-Lonhienne, C., Rennenberg, H., Lakshmanan, P., Schmidt, S., 2011. Nitrate paradigm does not hold up for sugarcane. PloS One 6, e19045.
Sexton, J., Everingham, Y., Inman-Bamber, N., Stokes, C., 2014. Climate change will impact the sugarcane industry in Australia, Proceedings of the South African Sugar Technologists Association.
Shanthi, R., Alarmelu, S., Mahadeva Swamy, H., Lakshmi Pathy, T., 2023. Impact of climate change on sucrose synthesis in sugarcane varieties, Agro-industrial. perspectives on sugarcane production under environmental stress. Springer, pp. 13–38.
Signor, D., Cerri, C.E.P., Conant, R., 2013. N_2O emissions due to nitrogen fertilizer applications in two regions of sugarcane cultivation in Brazil. Environ. Res. Lett. 8, 015013.
Singels, A., Jones, M., Marin, F., Ruane, A., Thorburn, P., 2013. Predicting climate change impacts on sugarcane production at sites in Australia, Brazil and South Africa using the Canegro model. Sugar Tech. 16, 347–355.
Singels, A., Jones, M., Marin, F., Ruane, A., Thorburn, P., 2014. Predicting climate change impacts on sugarcane production at sites in Australia, Brazil and South Africa using the Canegro model. Sugar Tech. 16, 347–355.
SRA, 2008. Improv. Environ. Outcomes Profitab. Innov. Manag. Nitrogen. ⟨https://elibrary.sugarresearch.com.au/items/67bb7913-2210-4996-b8bf-75896a0cb2f8⟩.
SRA, 2014. A Rev. Nitrogen Use Effic. Sugarcane. ⟨https://elibrary.sugarresearch.com.au/⟩.
SRA, 2017. Oppor. Energy Innov. Aust. Irrig. Sugarcane. ⟨https://sugarresearch.com.au/sugar_files//2018/01/Energy-in-irrigated-cane_2017x.pdf⟩.
SRA, 2022. Nutr. Manag. Guidel. Sugarcane N. South Wales. ⟨https://sugarresearch.com.au/⟩.
SugarAustralia, 2025. Sugar Ind. ⟨https://sugaraustralia.com.au/our-business/the-sugar-industry⟩.
SunshineSugar, 2022. Ref. Notes N. cane Grow. NSW. ⟨https://www.sunshinesugar.com.au/wp-content/uploads/2022/01/Reference-notes-NSW-New-Growers-2022_.pdf⟩.
SunshineSugar, 2023. Var. Product. Rep. ⟨https://growers.sunshinesugar.com.au/cane-varieties/variety-productivity-reports.html⟩.
SunshineSugar, 2025. Sustainability. ⟨https://www.sunshinesugar.com.au/sustainability/paddock-to-pack/⟩.
Takeda, N., Friedl, J., Rowlings, D., De Rosa, D., Scheer, C., Grace, P., 2021. Exponential response of nitrous oxide (N_2O) emissions to increasing nitrogen fertiliser rates in a tropical sugarcane cropping system. Agric. Ecosyst. Environ. 313, 107376.
Tanner, C., Sinclair, T., 1983. Effic. Water Use Crop Prod. Res. re-Search? Limit. Effic. Water Use Crop Prod. 1–27.
Thompson, M., Poggio, M., Farr, M., Power, B., Shaw, M., Telford, P., Neelamraju, C., 2024. Econ. Eval. Sugarcane Manag. Pract. that Improv. Water Qual. Tech. Rep.
Thorburn, P., Biggs, J., Attard, S., Kemei, J., 2011a. Environmental impacts of irrigated sugarcane production: nitrogen lost through runoff and leaching. Agric. Ecosyst. Environ. 144, 1–12.
Thorburn, P.J., Biggs, J.S., Webster, A.J., Biggs, I.M., 2011b. An improved way to determine nitrogen fertiliser requirements of sugarcane crops to meet global environmental challenges. Plant Soil 339, 51–67.
Thorburn, P.J., Park, S.E., Biggs, I., 2003. Nitrogen fertiliser management in the Australian sugar industry: Strategic opportunities for improved efficiency. 2003 Conference of the Australian Society of Sugar Cane Technologists, Townsville, Queensland, Australia.
Thorburn, P., Wilkinson, S., 2013. Conceptual frameworks for estimating the water quality benefits of improved agricultural management practices in large catchments. Agric. Ecosyst. Environ. 180, 192–209.
Topp, V., Litchfield, F., Coelli, R., Ashton, D., 2022. Financial performance of sugarcane farms 2020-21–2021-22. ABARES, Canberra, December. ⟨https://www.agriculture.gov.au/abares/research-topics/surveys/sugar#download⟩.
USDA, 2023. Sugar Annual. ⟨https://apps.fas.usda.gov/newgainapi/api/Report/DownloadReportByFileName?fileName=Sugar+Annual_Canberra_Australia_AS2022-0009.pdf⟩.
Vallis, I., Catchpoole, V., Hughes, R., Myers, R., Ridge, D., Weier, K., 1996. Recovery in plants and soils of 15N applied as subsurface bands of urea to sugarcane. Aust. J. Agric. Res. 47, 355–370.
Verma, A.K., Garg, P.K., Prasad, K.H., Dadhwal, V.K., 2023. Variety-specific sugarcane yield simulations and climate change impacts on sugarcane yield using DSSAT-CSM-CANEGRO model. Agric. Water Manag. 275, 108034.
Vu, J.C., Allen Jr, L.H., Gesch, R.W., 2006. Up-regulation of photosynthesis and sucrose metabolism enzymes in young expanding leaves of sugarcane under elevated growth CO_2. Plant Sci. 171, 123–131.
Webster, A., Thorburn, P., Roebeling, P., Horan, H., Biggs, J., 2009. The expected impact of climate change on nitrogen losses from wet tropical sugarcane production in the Great Barrier Reef region. Mar. Freshw. Res. 60, 1159–1164.
Wei, X., Eglinton, J., Piperidis, G., Atkin, F., Morgan, T., Parfitt, R., Hu, F., 2022. Sugarcane breeding in Australia. Sugar Tech. 24, 151–165.
Wiedenfeld, R.P., 1995. Effects of irrigation and N fertilizer application on sugarcane yield and quality. Field Crops Res. 43, 101–108.
Wu, L., Wang, B., Quan, H., Li Liu, D., Feng, H., Chen, F., Wu, L., 2025. Designing virtual maize cultivars with optimal planting date and density can improve yield and water use efficiency under plastic mulching conditions. Field Crops Res. 322, 109723.
Yang, Y., Liu, D.L., Anwar, M.R., O'Leary, G., Macadam, I., Yang, Y., 2016. Water use efficiency and crop water balance of rainfed wheat in a semi-arid environment: sensitivity of future changes to projected climate changes and soil type. Theor. Appl. Climatol. 123, 565–579.
Yang, L., Zhou, Y., Meng, B., Zhan, J., Xi, M., Deng, Y., Wu, W., Lakshmanan, P., Chen, X., Zhang, F., 2024. High sugarcane yield and large reduction in reactive nitrogen loss can be achieved by lowering nitrogen input. Agric. Ecosyst. Environ. 369, 109032.
Yao, S., Liu, D.L., Wang, B., Webb, J.K., Li, S., Huete, A., Xiang, K., Yu, Q., 2026. Climate warming enhances sugarcane yield and increases annual harvest frequency in northern coastal New South Wales, Australia. Agric. Syst. 231, 104502.
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, 353.
Zhao, Z., Verburg, K., Huth, N., 2017. Modelling sugarcane nitrogen uptake patterns to inform design of controlled release fertiliser for synchrony of N supply and demand. Field Crops Res. 213, 51–64.