Agricultural Systems 231 (2026) 104502

Contents lists available at ScienceDirect

Agricultural Systems

journal homepage: www.elsevier.com/locate/agsy

Research Paper

Climate warming enhances sugarcane yield and increases annual harvest frequency in northern coastal New South Wales, Australia

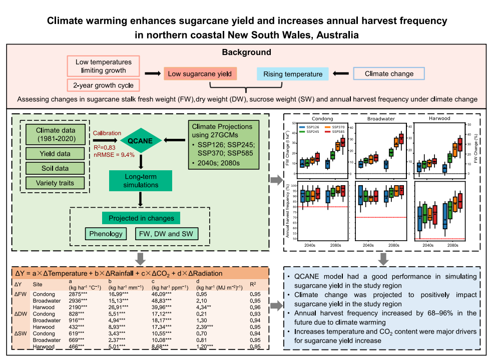
Shijin Yao[a,b], De Li Liu[b,c,d,*], Bin Wang[b,d,e,*], Jonathan K. Webb[a], Siyi Li[f], Alfredo Huete[a], Keyu Xiang[a,b], Qiang Yu[g]

[a] School of Life Sciences, Faculty of Science, University of Technology Sydney, PO Box 123, Broadway, Sydney, NSW 2007, Australia
[b] NSW Department of Primary Industries, Wagga Wagga Agricultural Institute, Wagga Wagga, NSW 2650, Australia
[c] Climate Change Research Centre, University of New South Wales, Sydney, NSW 2052, Australia
[d] Gulbali Institute for Agriculture, Water and Environment, Charles Sturt University, Wagga Wagga, NSW 2650, Australia
[e] Hawkesbury Institute for the Environment, Western Sydney University, Richmond, NSW, Australia
[f] The University of Queensland, School of Agriculture and Food Sustainability, St Lucia, Queensland 4072, Australia
[g] State Key Laboratory of Soil Erosion and Dryland Farming on the Loess Plateau, Institute of Soil and Water Conservation, Northwest A&F University, Xianyang 712100, China

HIGHLIGHTS

- QCANE model accurately simulated sugarcane yield in the study region.
- Climate change was projected to increase sugarcane yield in the study region.
- Annual harvest frequency increased to 68–96 % in the future due to climate warming.
- Increased yields were mainly driven by rising temperature and CO_2 concentration.

GRAPHICAL ABSTRACT



ARTICLE INFO

Editor: Leonard Rusinamhodzi

Keywords:
Sugarcane
QCANE model
Climate change
Harvest frequency
Australia

ABSTRACT

CONTEXT: Australia is a leading exporter of raw sugar on the global market. Rising temperatures could enable sugarcane to achieve harvestable yields in a 1-year growth cycle instead of the traditional 2-year cycle in the subtropical regions of northern New South Wales (NSW). However, no study has evaluated how climate change impacts annual harvest frequency, leaving a critical gap in understanding sugarcane production's future in Australia.
OBJECTIVE: We aim to quantify the impacts of climate change on sugarcane yield and annual harvest frequency and identify the main climatic drivers that determine yield change.
METHODS: We used sugarcane yield data collected from three milling regions, Condong, Broadwater, and Harwood, to validate the QCANE sugarcane model in northern coastal NSW. The validated model was then driven by climate data downscaled from 27 global climate models under the Coupled Model Intercomparison Project Phase 6 to simulate sugarcane growth and sugar accumulations.

* Corresponding authors at: NSW Department of Primary Industries, Wagga Wagga Agricultural Institute, Wagga Wagga, NSW 2650, Australia.
E-mail addresses: de.li.liu@dpi.nsw.gov.au (D.L. Liu), bin.a.wang@dpi.nsw.gov.au (B. Wang).

https://doi.org/10.1016/j.agsy.2025.104502
Received 23 March 2025; Received in revised form 29 August 2025; Accepted 1 September 2025
Available online 11 September 2025

RESULTS AND CONCLUSIONS: The QCANE model showed strong agreement between simulated and observed values, with an R^2 of 0.83 for stalk fresh weight (FW) and 0.80 for sucrose weight (SW), and nRMSE values of 9.4 % for FW and 10.0 % for SW. Under rising emissions (SSP126 to SSP585), yield projections indicated increases by the end of the 21st century, with FW rising by 6–34 Mg ha^{-1} (i.e., 6–29 %), biomass dry weight (DW) by 2–11 Mg ha^{-1} (6–29 %), and SW by 1–7 Mg ha^{-1} (10–46 %) across the three study sites. Additionally, the annual harvest frequency was expected to increase from 50 to 80 % during the baseline period (1981–2020) to 68–96 %, with a greater proportion of future years supporting frequent annual harvests. Climate variables accounted for 93–96 % of the yield variation, with elevated atmospheric CO_2 concentration as the dominant contributor to yield increases.

SIGNIFICANCE: These findings highlight opportunities to enhance sugarcane production by adopting a 1-year harvest cycle under future climate conditions, providing valuable insights for the sugarcane industry to adapt and thrive in the face of climate change.

1. Introduction

Sugarcane (Saccharum spp.) is a crucial crop for global food and energy production (Dias and Inman-Bamber, 2020; Jackson et al., 2014). It is cultivated year-round in tropical and subtropical regions across more than 100 countries, spanning 27.55 million hectares globally (FAOSTAT, 2023; Sanches et al., 2023). However, sugarcane productivity is highly sensitive to climate variations, including temperature, CO_2 concentrations [CO_2], and rainfall, which influences yield and growth cycles (Shanthi et al., 2023; Yao et al., 2025; Zhao and Li, 2015). Accurately assessing the impact of climate change on sugarcane is essential for developing resilient and adaptive strategies to maximize yields.

Australia is a major global exporter of raw sugar and sugar by-products, ranking as the fourth-largest exporter of raw sugar after Brazil, Thailand, and India (USDA, 2022). Sugarcane in Australia is mainly cultivated along the eastern coastline, spanning approximately 2100 km from the tropical regions of Queensland to the subtropical areas of northern New South Wales (NSW) (USDA, 2023; Wei et al., 2022). Temperature is a dominant factor influencing sugarcane yield and the growth cycle in these regions (Muchow et al., 1999; Park et al., 2008). In the tropical north, favorable warm conditions support annual sugarcane harvesting, whereas in subtropical NSW, lower autumn and spring temperatures restrict sugarcane growth, extending the crop cycle to two years (SRA, 2024; SunshineSugar, 2022). Climate models have predicted that temperatures in the sugarcane-growing regions in northern coastal NSW are likely to rise by approximately 1.7 °C in the near-future (by 2059) and by about 3.4 °C in the far-future (by 2099) under high emissions (SSP3–7.0) (AdaptNSW, 2024b). If these warming trends occur, sugarcane growers may be able to achieve harvestable yields within a 1-year growth cycle instead of the traditional 2-year cycle. However, despite the potential benefits of warmer conditions, future rainfall is projected to decline by 3 %–11.5 % from 2059 to 2099 (AdaptNSW, 2024b), which may pose challenges for maintaining yield increases. Given these uncertainties in temperature-driven growth acceleration and potential water limitations, no study has yet assessed the impact of climate change on annual harvest frequency in NSW. This highlights a critical gap in understanding the future of sugarcane production in the region.

Process-based sugarcane growth models simulate underlying biophysical processes, offering reliable predictions of sugarcane growth, yield, and resource use efficiency under varying environmental and management conditions (Junior et al., 2022; Marin and Jones, 2014). Prominent models include the South African CANEGRO model (Inman-Bamber, 1991; Inman-Bamber et al., 1993), the Brazilian SAMUCA model (dos Santos Vianna et al., 2020; Marin et al., 2017; Marin and Jones, 2014), and the Australian models QCANE (Liu and Bull, 2001) and APSIM-Sugarcane (Keating et al., 1999; Wegener et al., 1988). These models were used to simulate sugarcane growth and production under different climatic scenarios. For instance, Singels et al. (2014) applied the CANEGRO model to project the impact of increases in [CO_2] and temperature on sugarcane yield at a global scale. Their result indicated that stalk fresh weight (FW) was expected to increase in Brazil and South Africa, with approximately half of the yield changes attributed to the fertilization effect of elevated [CO_2]. Using the SAMUCA model, dos Santos Vianna et al. (2020) simulated the effects of a green cane trash blanket (GCTB) on sugarcane growth and water use, demonstrating that GCTB can substantially increase yields in dry climates and reduce water use across environments. In Southern China, Zu et al. (2018) applied the QCANE model to simulate potential yields and yield gaps of sugarcane, highlighting nitrogen stress as the dominant driver of the yield gap due to generally abundant precipitation in the region. In Australia, Park et al. (2008) employed the APSIM-Sugarcane model to project climate change impacts on sugarcane yield, suggesting that elevated temperature and [CO_2], in combination with moderate to high rainfall, could enhance sugarcane yield.

While these widely used models provide valuable frameworks for simulating sugarcane growth, they have notable limitations. For example, APSIM-Sugarcane provides a simple and computationally efficient framework by using radiation use efficiency to drive daily dry matter accumulation. However, it does not explicitly account for respiration (Marin et al., 2015), which becomes increasingly important in later growth stages as greater biomass leads to higher maintenance respiration losses and reduced growth (van Heerden et al., 2010). This limitation is particularly relevant under climate change scenarios, as respiration is highly sensitive to rising temperatures and may offset the potential benefits of enhanced growth conditions (Bonnett et al., 2006; Singels et al., 2014). Similarly, CANEGRO converts intercepted photosynthetically active radiation into gross photosynthate using a conversion efficiency adjusted for water, temperature, and CO_2 (Marin et al., 2015). However, sucrose accumulation in CANEGRO is empirically simulated based on physiological age, temperature, and water stress, without an explicit linkage to the carbon balance via direct carbon flow from assimilates (Jones et al., 2011; Marin et al., 2023; Singels et al., 2008). This simplification limits the model's capacity to represent the dynamic interactions among photosynthesis, respiration, and carbohydrate allocation. These processes become increasingly critical under climate change conditions, where elevated CO_2, rising temperatures, and variable water availability interact to influence carbon assimilation and partitioning. In the SAMUCA model, it incorporates a detailed representation of soil-plant-atmosphere interactions and a CO_2-responsive photosynthesis function, allowing for more flexible and realistic simulation of climate change impacts. It enables accurate simulation of sugarcane growth, particularly under green cane trash blanket conditions in both water-limited and irrigated systems across a range of climate scenarios (dos Santos Vianna et al., 2024; dos Santos Vianna et al., 2020; Marin and Jones, 2014). However, similar to CANEGRO, sucrose accumulation in SAMUCA is still primarily modeled as a function of air temperature and soil moisture (Marin and Jones, 2014), lacking a fully integrated carbon flow mechanism. In contrast, QCANE provides more comprehensive physiological representation by integrating canopy development, photosynthesis, respiration, and dynamic carbohydrate partitioning among plant organs for growth and maintenance, all influenced by phenological development and environmental factors (Liu, 1996; Liu and Bull, 2001; Liu and Helyar, 2003; Liu et al., 1998).

In this study, we used collected sugarcane yield data from three milling regions, Condong, Broadwater, and Harwood in NSW to validate the sugarcane model of QCANE. The validated model was driven by climate data downscaled from 27 global climate models (GCMs) under the Coupled Model Intercomparison Project Phase 6 to simulate sugarcane yield under future climate in NSW. We aim to: (1) assess the potential impacts of CO_2, temperature, rainfall, and global solar radiation on sugarcane yield, (2) explore the possibility of increasing annual harvest frequency under different future climate scenarios, and (3) quantify the contribution of climatic factors to yield change. We anticipate that the results will provide valuable insights for optimizing sugarcane production and developing effective adaptation strategies to sustain sugarcane production in NSW under climate change.

2. Materials and methods

2.1. Study area

The sugarcane-growing region in NSW encompasses three key locations (corresponding to three sugar mills), Condong, Harwood, and Broadwater, all of which were included in this study. These sites are located in northern coastal NSW (Fig. 1a), characterized by a typical subtropical climate with substantial rainfall in summer and drier conditions in winter (Liu et al., 2021). Among the three sites, Condong, the northernmost location, is the warmest and wettest, with an average annual temperature of 20.4 °C and annual rainfall of 1683 mm. Temperature and rainfall gradually decrease southward, with Broadwater and Harwood having a lower mean temperature of 19.9 °C. Broadwater receives 1627 mm of annual rainfall, while Harwood, the southernmost site, has the lowest annual rainfall at 1314 mm (Fig. 1b).

2.2. Climate data

Historical daily climate data (1981–2020), including maximum temperature, minimum temperature, rainfall, and global solar radiation, sourced from the SILO (Scientific Information for Land Owners) point climate dataset (Jeffrey et al., 2001) for the three geographically closest climate stations to the sites of Condong, Broadwater, and Harwood. Future climate projections for the same variables were derived from 27 Global Climate Models (GCMs) (Table 1, https://esgf-node.llnl.gov/search/cmip6/) from the Coupled Model Intercomparison Project Phase 6 (CMIP6, https://pcmdi.llnl.gov/CMIP6/). Daily climate data for each location was statistically downscaled using the NWAI-WG (Liu and Zuo, 2012). The downscaling process involved two steps: spatial and temporal downscaling. First, monthly GCM projections were interpolated to site using inverse distance weighting, followed by bias correction via quantile mapping to align with observed data (Zhang, 2005; Zhang, 2007). Second, the bias-corrected monthly data were disaggregated into daily values using the modified WGEN weather generator (Richardson and Wright, 1984). These projected climate data have been widely used in numerous climate impact studies (Guga et al., 2023; Wang et al., 2022; Zhu et al., 2024).

CMIP6 integrates the scientific combination scenarios of shared socioeconomic paths (SSPs), and representative concentrated paths (RCPs) into the impact of socio-economic development, providing a range of

Table 1
List of 27 global climate models (GCMs) used for climate projections in the study.

Model ID	Name of GCM	Institute ID	Country
01	ACCESS-CM2	BoM	Australia
02	ACCESS-ESM1–5	BoM	Australia
03	BCC-CSM2-MR	BCC	China
04	CIESM	THU	China
05	CMCC-CM2-SR5	CMCC	Italy
06	CNRM-CM	CNRM	France
07	CNRM-CM6–1-HR	CNRM	France
08	CNRM-ESM	CNRM	France
09	CanESM5	CCCMA	Canada
10	CanESM5-CanOE	CCCMA	Canada
11	EC-Earth3	EC-EARTH	Europe
12	EC-Earth3-Veg	EC-EARTH	Europe
13	FGOALS-g3	FGOALS	China
14	GFDL-ESM4	NOAA GFDL	USA
15	GFDL-CM4	NOAA GFDL	USA
16	GISS-E2–1-G	NASA GISS	USA
17	HadGEM3-GC31LL	MOHC	UK
18	INM-CM4–8	INM	Russia
19	INM-CM5–0	INM	Russia
20	IPSL-CM	IPSL	France
21	MIROC-ES2L	MIROC	Japan
22	MIROC6	MIROC	Japan
23	MPI-ESM1–2-HR	MPI-M	Germany
24	MPI-ESM1–2-LR	MPI-M	Germany
25	MRI-ESM2–0	MRI	Japan
26	NESM3	NUIST	China
27	UKESM1–0-LL	Met Office	UK

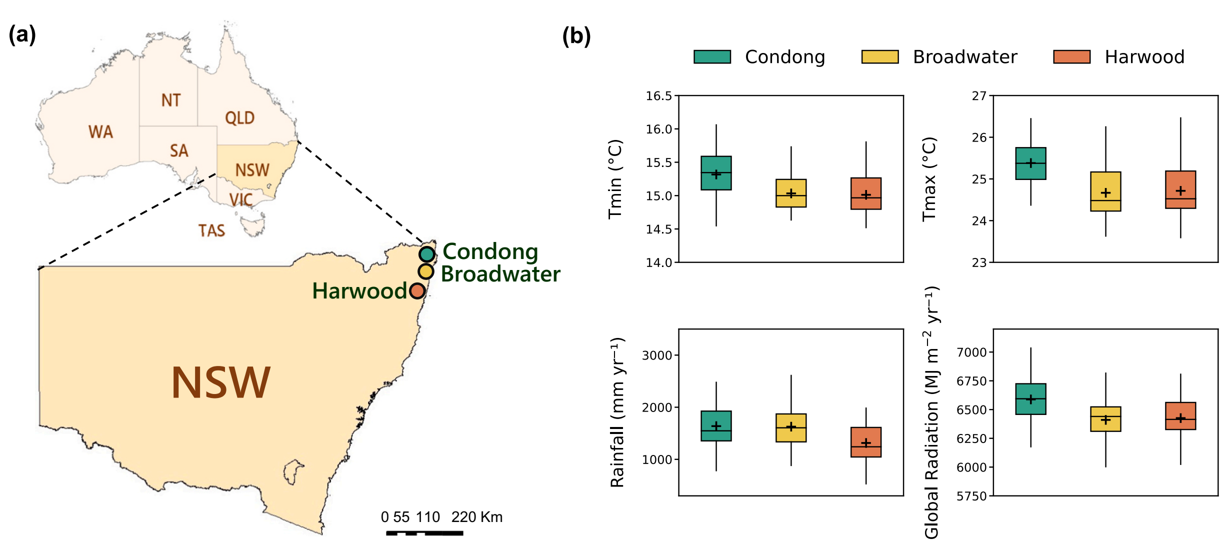


Fig. 1. (a) Geographic location of Condong, Broadwater, and Harwood in northern coastal NSW. (b) Long-term average annual climate during the baseline period (1981–2020), including minimum temperature (Tmin), maximum temperature (Tmax), total annual rainfall, and global solar radiation.

distinct end-of-century climate change outcomes (Database, S, 2018). In this study, we used four representative SSPs to cover a range from low to high emissions: the "sustainability" scenario (SSP1–2.6), the "middle of the road" scenario (SSP2–4.5), the "regional rivalry" scenario (SSP3–7.0), and the "fossil-fueled development" scenario (SSP5–8.5) (IPCC, 2021). By the end of the 21st century, SSP1–2.6 (hereafter SSP126) is projected to have a CO_2 concentration of approximately 450 ppm. SSP2–4.5 (SSP245) is expected to increase to around 560 ppm, SSP3–7.0 (SSP370) to about 810 ppm, and SSP5–8.5 (SSP585) to approximately 1100 ppm, assuming no mitigation measures are implemented (IPCC, 2021).

This study evaluated the impacts of changing climate on sugarcane production during the two future periods of the 2040s (2021–2060) and 2080s (2061–2100), relative to the baseline period (1981–2020). Yearly atmospheric [CO_2] (ppm) from 1981 to 2100 was calculated and integrated into the QCANE simulation using empirical equations derived through non-linear least-squares regression (Liu et al., 2017). These equations were based on the concentration pathways provided by the Scenario Model Intercomparison Project (ScenarioMIP) for CMIP6 (O'Neill et al., 2016), and are presented as follows:

$$[CO_2]_{SSP126} = 113.08 - \frac{34.344 - 0.010402y}{0.15585 - 0.043727y^{0.28905}} + 4.5948(y - 1961) - 0.023987(y - 1977)^2 - 2.4959 \times 10^{-4}(y - 2054)^3 - 6.5721 \times 10^{-7}(y - 2054)^4 \quad (1)$$

$$[CO_2]_{SSP245} = 62.044 + \frac{34.002 - 3.8702y}{0.24423 - 1.1542y^{2.4901}} + 0.028057(y - 1900)^2 + 0.00026827(y - 1960)^3 - 9.2751 \times 10^{-7}(y - 1910)^4 - 2.2448(y - 2030) \quad (2)$$

$$[CO_2]_{SSP370} = 151.9 + \frac{20.092 + 10.315y}{5.8491 + 2.4884y^{2.268}} + 4.752 \times 10^{-5}(y - 143.55)^2 + 1.037 \times 10^{-4}(y - 1908)^3 - 5.9113 \times 10^{-8}(y - 1849)^4 \quad (3)$$

$$[CO_2]_{SSP585} = 757.44 + \frac{84.938 - 1.537y}{2.2011 - 3.8289y^{-0.45242}} + 2.4712 \times 10^{-4}(y + 15)^2 + 1.9299 \times 10^{-5}(y - 1937)^3 + 5.1137 \times 10^{-7}(y - 1910)^4 \quad (4)$$

where the variable y represents the calendar year spanning from 1981 to 2100. In Eq. (4), the term "y + 15" reflects a curve-fitting adjustment introduced during non-linear least-squares regression of the SSP585 CO_2 concentration pathway.

2.3. Model description and simulations

2.3.1. The QCANE model

QCANE is a process-based sugarcane growth model developed by Liu and Bull (2001). In QCANE, daily gross photosynthesis is determined by diurnal light variation and light attenuation (Liu, 1996), influenced by factors such as leaf nitrogen and temperature. By employing a detailed process-based approach (Liu and Bull, 2001; Liu and Kingston, 1995), QCANE directly links CO_2 concentration to the photosynthesis function, enhancing its flexibility in simulating the effects of climate change on photoassimilates. In QCANE, physiological and biochemical processes in sugarcane growth and development are integrated using a source-sink approach. A key feature of this model is the central role of sucrose, which serves as a carbon pool to supply daily structural-C and maintenance-C requirements (Liu and Bull, 2001).

The effect of CO_2 on photosynthesis is modeled by modification of the method proposed by Reyenga et al. (1999), which incorporated the interaction between CO_2 concentration and temperature:

$$f = \frac{(C_e - \Gamma)(350 + 2\Gamma)}{(C_e + 2\Gamma)(350 - \Gamma)} \quad (5)$$

$$where\ \Gamma = 25 + \frac{34t^2}{350 + t^2} \quad (6)$$

In Eq. (5), f is the photosynthetic enhancement factor, representing the relative change in photosynthesis under elevated CO_2 concentrate (Ce) and temperature (t), rather than the absolute photosynthesis rate. The effects of CO_2 and temperature on f are illustrated in Fig. S2 and Fig. S3 (see Supplementary materials).

The partitioning of photoassimilates (CH_2O) into sugarcane's vegetative components (leaf, non-millable top, stalk, and root) is managed by accounting for daily growth, growth stage, and temperature (Liu and Bull, 2001). Respiration is divided into growth and maintenance portions, with the growth respiration rate set as a constant, considering that synthesis of three units of new tissue that costs one unit of CH_2O (Thornley and Johnson, 1990). Maintenance respiration (Rm) is determined as a function of accumulated biomass and temperature. The large biomass of sugarcane can lead to a high Rm loss in the late growth stages, directly contributing to the reduced growth phenomenon (RGP) associated with biomass accumulation (van Heerden et al., 2010). By accounting for RGP, QCANE can effectively simulate sugarcane growth and sucrose accumulation under different growth durations and environmental conditions. The model distinguishes plant and ratoon crops by initial leaf area index (0.008 vs. 0.08), reflecting stubble and root reserves from the preceding crop, and simulates chained crop cycles in which ratoon growth benefits from these carry-over effects. QCANE also incorporates row spacing as an input, as narrower rows intercept more radiation prior to canopy closure than wider rows, although such differences diminish once the canopy develops.

2.3.2. Model validation

The QCANE model was initially calibrated and validated by Liu and Bull (2001) in Bundaberg, Queensland (lat. 24.83°S, long.152.43°E), a subtropical region located north of the study sites (lat. 28.32–29.42°S, long.153.43–153.25°E). The parameters built into QCANE were originally reported by Liu and Bull (2001). In this study, we did not recalibrate the model; instead, we validated its performance by comparing simulated yields against available observations for the widely cultivated sugarcane variety Q208 in northern NSW. The data sources used for validation are provided in Table S1 (see Supplementary materials).

We used the coefficient of determination (R^2), root mean squared error (RMSE), and normalized root mean squared error (nRMSE) to evaluate the model's performance for both simulated and observed yields. These metrics are widely accepted and provide a comprehensive evaluation of model accuracy and fit (Feng et al., 2018; Li et al., 2022; Wang et al., 2022). As RMSE approaches 0, and R^2 approaches 1, predictions become increasingly accurate. When the value of nRMSE is below 20 %, the model is acceptable (Li et al., 2021). The model assessment indicators, R^2, RMSE, and nRMSE, were calculated as follows:

$$R^2 = 1 - \frac{SSR}{SST} \quad (7)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)^2} \quad (8)$$

$$nRMSE = \frac{RMSE}{\overline{O}} \times 100\% \quad (9)$$

where *SSR* (Sum of the Squared Residuals) represents the sum of the squared differences between each predicted value and the mean of the dependent variable, and *SST* (Total Sum of Squares) represents the total variance in the dependent variable. Here, O_i and P_i are the predicted and observed values, respectively, $\overline{O}$ represents the mean of the observed values, and n is the number of samples.

2.3.3. Long-term simulations

The QCANE model was used to quantify the potential impacts of future climate change on sugarcane productivity in NSW. Simulations were performed from 1981 to 2100 at the three study sites. We used a typical sugarcane growth cycle consisting of one plant crop followed by three ratoon crops (i.e., four harvests in total) before replanting, consistent with regional management practices in which up to eight years of cane production are implemented under a two-year harvest cycle (SunshineSugar, 2022). Irrigation is not usually applied in the NSW region (Topp et al., 2022), because of the high rainfall and presence of shallow water tables (Everingham et al., 2015). Therefore, the simulations were under rain-fed conditions without nitrogen stress.

To determine the harvest cycle, a sucrose weight (SW) threshold of 13.5 Mg ha^{-1} was defined, as extractable sugar is the primary product and key driver of profitability. Based on recent average sugar yields in NSW (SRA, 2024), this threshold determines whether sugarcane is harvested within a single year or allowed to grow further. If the SW exceeds 13.5 Mg ha^{-1} within a single year, the crop is harvested and classified as 1-year-old sugarcane. If the threshold is not met, the crop continues to grow into a second year to achieve a harvestable yield and is then classified as 2-year-old sugarcane. This approach reflects common sugarcane production practices in NSW (SRA, 2024). The sugarcane harvest season typically spans from June to November, with September being the predominant planting month across the three sites (SunshineSugar, 2022). To ensure consistency across scenarios and sites, a representative planting date of 1 Sep was selected, with the corresponding harvest date set to 31 Aug of the following year to define a 1-year or 2-year growth cycle. This standardized approach enabled consistent comparison of yield and harvest frequency across sites and scenarios, while minimizing the influence of management variability and isolating the effects of climate factors. This study used a widely cultivated sugarcane variety Q208 across three sites in NSW (SRA, 2024). Row spacing was set at 1.5 m.

2.4. Secondary bias correction

Biases in GCM data and limitations in the bias correction process during downscaling can result in discrepancies between GCM-derived climate data and observations (Haerter et al., 2011). To address this, a secondary bias correction is applied to further minimize residual biases that persist after the initial correction. This additional adjustment enhances the comparability of outputs from different GCMs, improving the reliability of impact assessments under future climate scenarios. In this study, this secondary bias correction was consistently applied to all simulated outputs driven by downscaled GCM data, following the method of Yang et al. (2016):

$$Bs = \overline{Y}_{GCM,b} - \overline{Y}_{obs,b} \tag{10}$$

$$Y = Y_{GCM} - Bs \tag{11}$$

where Bs represents the secondary bias, $\overline{Y}_{GCM,b}$ is the mean values of QCANE outputs over the baseline period (1981–2020) for simulations using downscaled GCM data, and $\overline{Y}_{obs,b}$ is that driven by observed climate data of the same period. Y is the output after applying the secondary bias correction, and Y_{GCM} is the QCANE simulated output driven by GCM data.

2.5. Statistical analysis of climate influences on yield

To quantify the effects of key climatic variables on projected changes in sugarcane yield under future scenarios, a multiple linear regression analysis was conducted (see Eq. (12)). The dependent variables were the projected changes in stalk fresh weight (ΔFW), above-ground biomass dry weight (ΔDW), and sucrose weight (ΔSW), relative to the baseline period (1981–2020) for the mid-future (2040s; 2021–2060) and far-future (2080s; 2061–2100) under SSP126, SSP245, SSP370, and SSP585 across the three study sites. Independent variables included projected changes in average temperature (ΔT, °C), total rainfall (ΔRf, mm), global solar radiation (ΔRad, MJ m^{-2}), and atmospheric CO_2 concentration (ΔCO_2, ppm). The regression model was specified as follows:

$$\Delta Y = a \times \Delta T + b \times \Delta Rf + c \times \Delta CO_2 + d \times \Delta Rad \tag{12}$$

where ΔY is the dependent variable (e.g., ΔFW, ΔDW, and ΔSW) and a–d are the fitted coefficients. Model performance was evaluated using the coefficient of determination (R^2), and statistical significance was assessed at levels of $P < 0.05$, 0.01, and 0.001.

To further quantify the relative contribution of each climatic variable to the variation in yield, partial coefficients of determination (partial R^2) were calculated for each factor. The partial R^2 for each variable was computed as:

$$\text{Partial } R^2 = \frac{R^2_{full} - R^2_{reduced}}{1 - R^2_{reduced}} \tag{13}$$

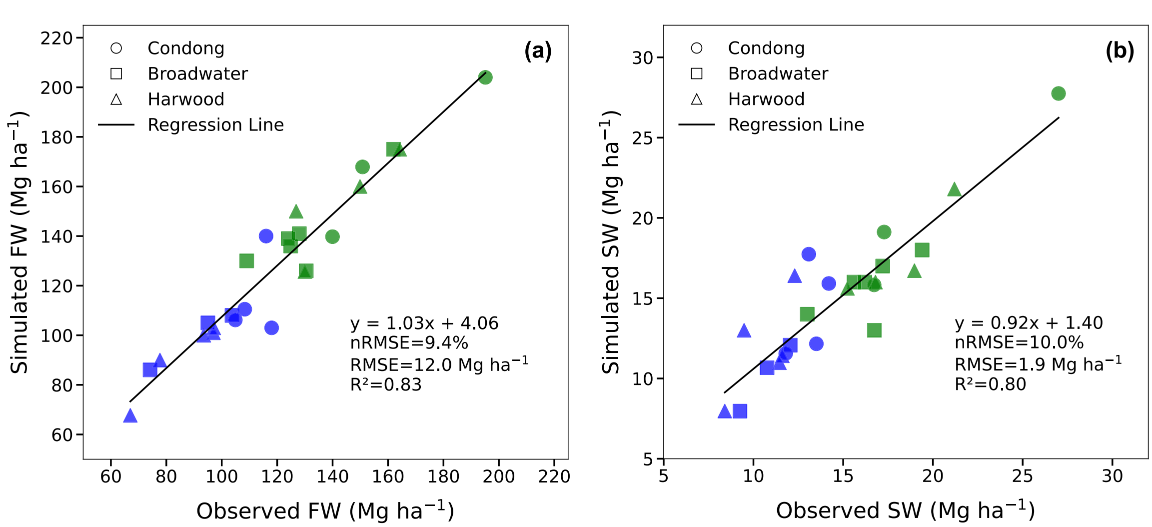


Fig. 2. Model validation of simulated versus observed sugarcane stalk fresh weight (FW, a) and sucrose weight (SW, b) across three sites. FW and SW points include both 1-year-old (blue) and 2-year-old (green) sugarcane crops. The observed data used for model validation is presented in Table S1 (see Supplementary materials). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

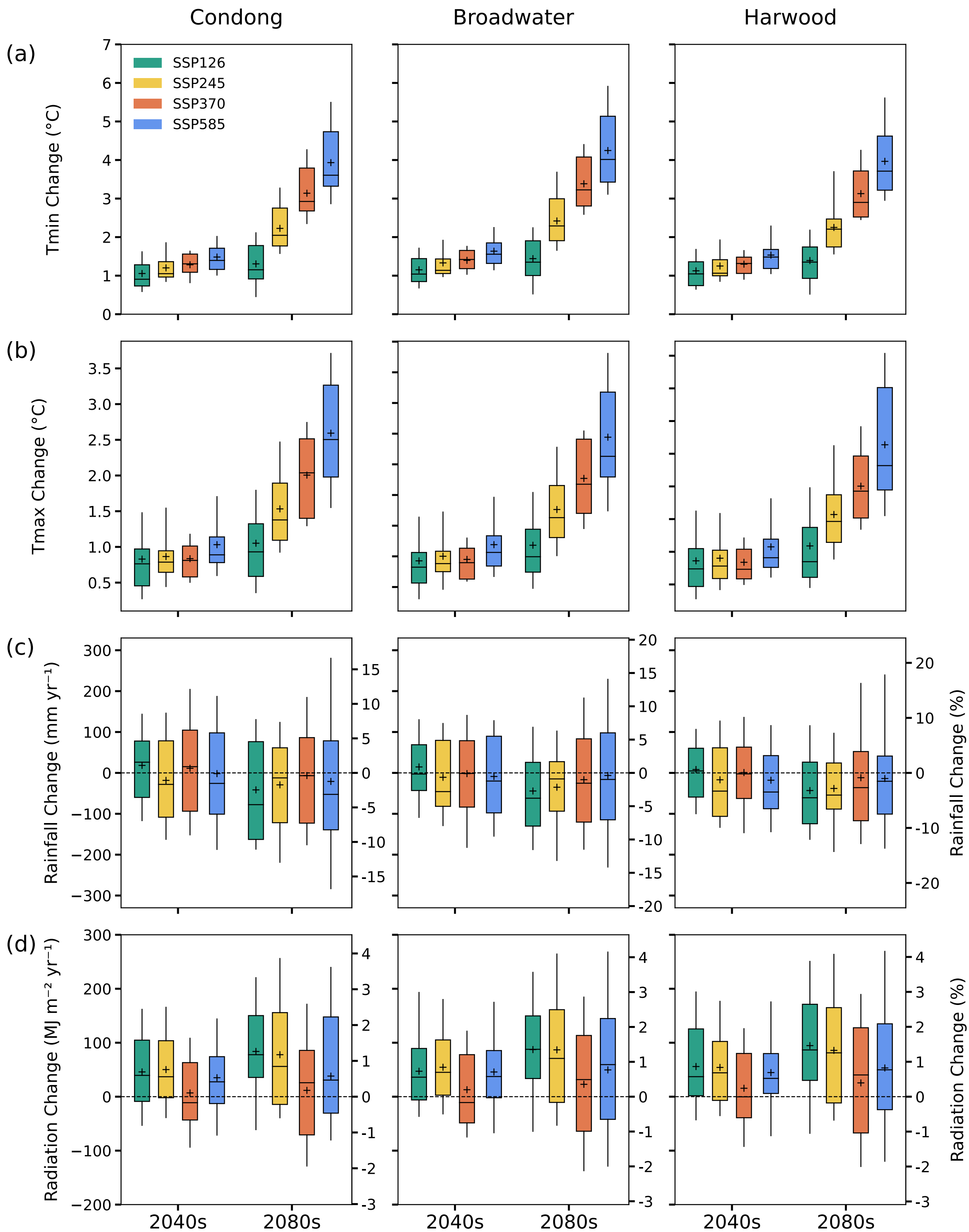


Fig. 3. Projected changes in annual mean minimum temperature (Tmin, a), maximum temperature (Tmax, b), rainfall (c), and global solar radiation (d) based on 27 GCMs under four scenarios (SSP126, SSP245, SSP370, and SSP585) for Condong, Broadwater, and Harwood in NSW. Changes are shown relative to the baseline period (1981–2020) for the mid-future (2040s; 2021–2060) and the far-future (2080s; 2061–2100). The boundaries of the boxes represent the 25th and 75th percentiles, while the whiskers extend to the 10th and 90th percentiles. The black line within each box indicates the multi-model median and the crosshair represents the multi-model mean. The 95 % confidence intervals of the mean are provided in the Fig. S4 (see Supplementary materials).

where R^2_{full} is the R^2 of the full model including all variables, and $R^2_{reduced}$ is the R^2 of a reduced model with the target variable removed.

3. Results

3.1. Model validation

The performance of the QCANE model was validated by comparing simulated values with observed values for stalk fresh weight (FW) and sucrose weight (SW). The results indicated high model accuracy, explaining 83 % ($R^2 = 0.83$) of the variance for FW and 80 % ($R^2 = 0.80$) for SW, with RMSE values of 12.0 Mg ha^{-1} for FW and 1.9 Mg ha^{-1} for SW (Fig. 2). Additionally, the regression slopes, ranging from 0.92 to 1.03, indicate strong alignment between simulated and observed data, with nRMSE values remaining below 10 %. These results enhance confidence in the QCANE model's reliability for simulating sugarcane growth in the study area.

3.2. Projected future climate

Across all three sites, both minimum and maximum temperatures were projected to increase over time under each emission scenario compared to the baseline (Fig. 3a–b). The incremental changes in minimum and maximum temperatures were projected to be most pronounced under SSP585, especially by the 2080s. Specifically, the smallest increase in minimum temperature based on the multi-GCM ensemble means was under SSP126 in the 2040s at 1.1 °C, while the largest increase was under SSP585 in the 2080s reaching 4.1 °C across the three sites (Fig. 3a). In contrast, changes in maximum temperature were projected to be slightly lower than those in minimum temperature across all scenarios, with increases between 0.9 °C and 2.7 °C (Fig. 3b).

In contrast to temperature, projected changes in rainfall exhibited substantial variability among the 27 GCMs across all SSP scenarios, as reflected in the large difference between the 10th and 90th percentiles (Q90 − Q10). Some GCMs projected increases, while others indicated decreases (Fig. 3c). For example, the greatest variability was observed under SSP585 in the 2080s at Condong, where projections ranged from −285 mm to 281 mm among the 27 GCMs. Despite this variation, the multi-GCM ensemble means projected minimal changes in annual rainfall, ranging from −1 % to 0.9 % across all scenarios by the 2040s, and from −3 % to −1 % by the 2080s relative to the baseline period, with the largest reduction occurring under SSP126.

Relative to the baseline, the multi-GCM ensemble means projected a

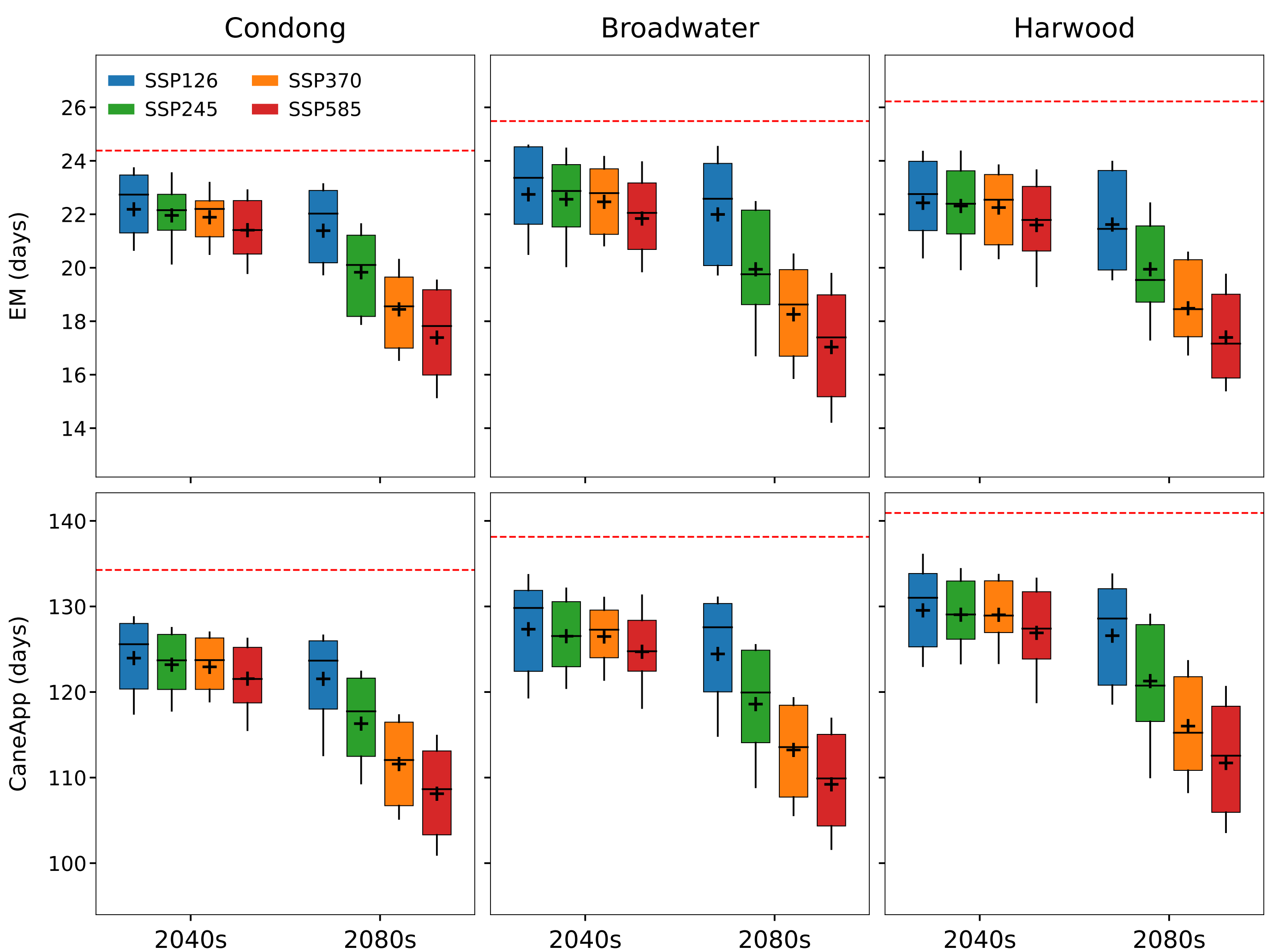


Fig. 4. Projected durations of phenological stages of emergence (EM, a) and cane appearance (CaneApp, b) based on 27 GCMs under four scenarios (SSP126, SSP245, SSP370, and SSP585) for Condong, Broadwater, and Harwood in NSW during the mid-future (2040s; 2021–2060) and the far-future (2080s; 2061–2100). The boundaries of the boxes represent the 25th and 75th percentiles, while the whiskers extend to the 10th and 90th percentiles. The black line within each box indicates the multi-model median and the crosshair represents the multi-model mean. The red dashed lines represent the baseline durations of EM and CaneApp during the historical period (1981–2020). The 95 % confidence intervals of the mean are provided in the Fig. S5 (see Supplementary materials). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

slight increase in future global solar radiation across all scenarios and sites, with a more pronounced rise in the 2080s (Fig. 3d). In the 2040s, the projected increase ranged from 0.2 % to 0.8 %, with the smallest change under SSP370. In the 2080s, the increase ranged from 0.3 % to 1.4 %. Consistently, SSP370 showed the smallest increase.

3.3. Sugarcane phenology changes under climate change

Fig. 4. illustrates the projected duration of two key sugarcane growth stages: emergence (from planting/ratoon to emergence, EM) and tillering (from emergence to cane appearance, CaneApp). The baseline simulations for 1981–2020 indicate that the EM stage lasted an average of 26 ± 2 days, while the CaneApp stage spanned approximately 137 ± 12 days across the three sites. Under future climate scenarios, both EM and CaneApp stages were projected to shorten across all sites, with greater reductions in the far future under higher emission scenarios. By the 2040s, the EM stage was expected to decrease to 22 days across all emission scenarios. By the 2080s, it was projected to shorten further to 20, 18, and 17 days under SSP245, SSP370, and SSP585, respectively, while SSP126 remained unchanged from the 2040s. The averaged EM stage in the 2080s was projected to be 19 days, with a reduction of 7 days compared to the baseline period. Similarly, the CaneApp stage was

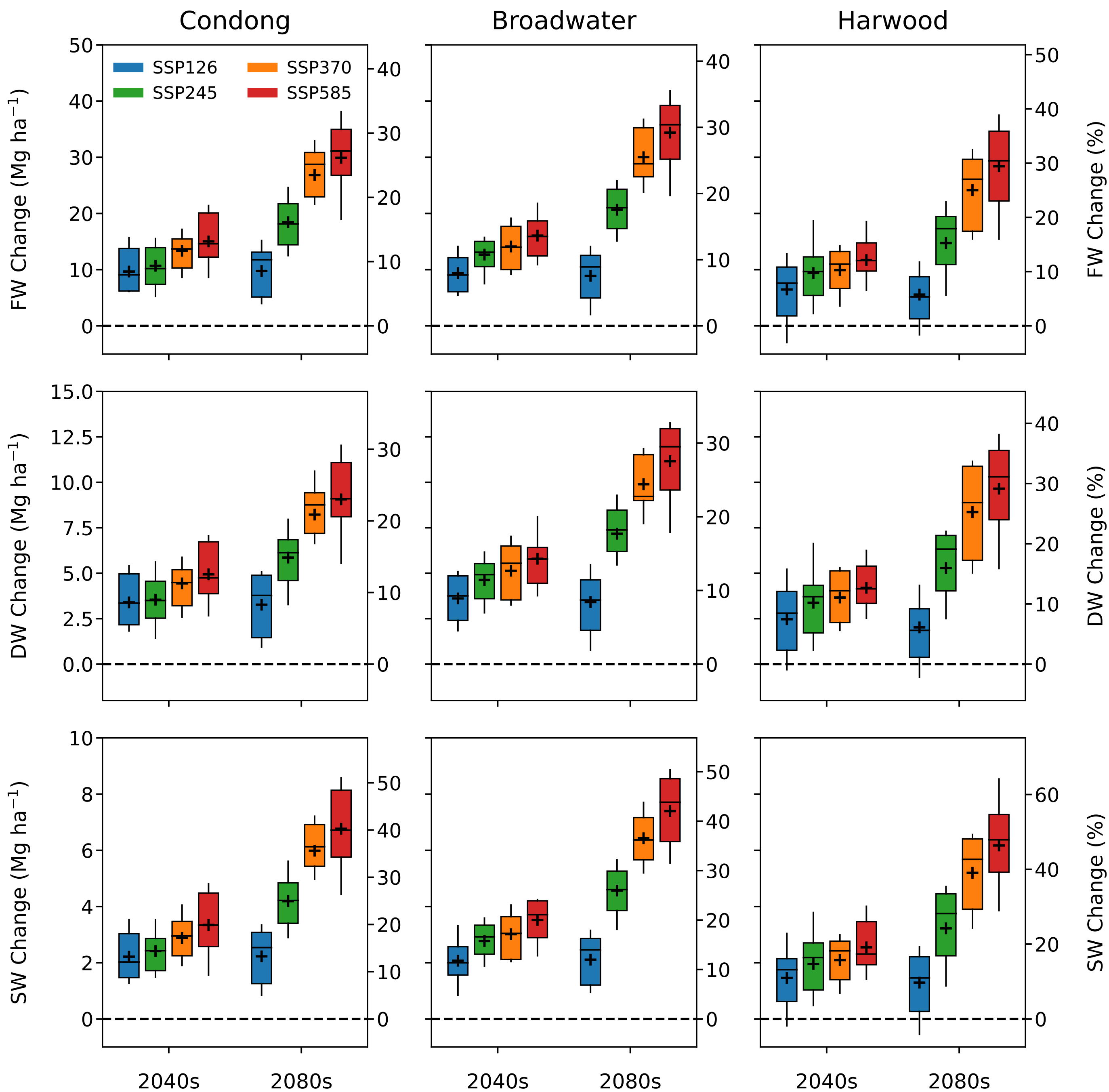


Fig. 5. Projected changes in stalk fresh weight (FW, a), above-ground biomass dry weight (DW, b), and sucrose weight (SW, c) based on 27 GCMs under four scenarios (SSP126, SSP245, SSP370, and SSP585) for Condong, Broadwater, and Harwood in NSW. Changes are shown relative to the baseline period (1981–2020) for the mid-future (2040s; 2021–2060) and the far-future (2080s; 2061–2100). The left-hand y-axis indicates changes in absolute values, and the right-hand y-axis shows percentage changes. The boundaries of the boxes represent the 25th and 75th percentiles, while the whiskers extend to the 10th and 90th percentiles. The black line within each box indicates the multi-model median and the crosshair represents the multi-model mean. The 95 % confidence intervals of the mean are provided in the Fig. S6 (see Supplementary materials).

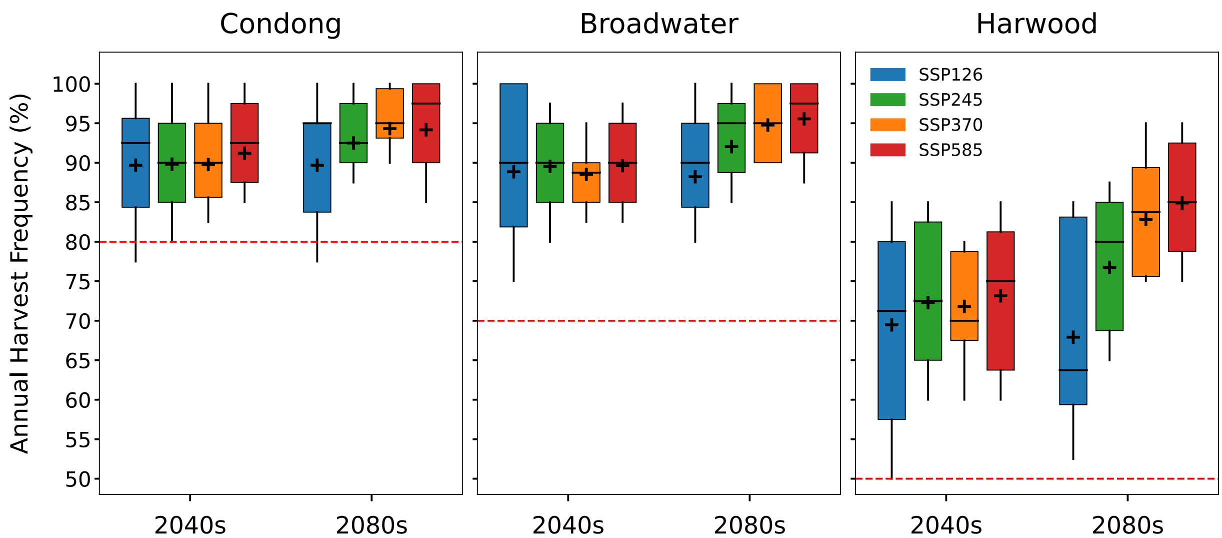


Fig. 6. Projected annual harvest frequency (%) based on 27 GCMs under four scenarios (SSP126, SSP245, SSP370, and SSP585) for Condong, Broadwater, and Harwood in NSW during the mid-future (2040s; 2021–2060) and the far-future (2080s; 2061–2100). The red dashed lines represent the annual harvest frequency during the baseline period (1981–2020). The boundaries of the boxes represent the 25th and 75th percentiles, while the whiskers extend to the 10th and 90th percentiles. The black line within each box indicates the multi-model median and the crosshair represents the multi-model mean. The 95 % confidence intervals of the mean are provided in the Fig. S7 (see Supplementary materials). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

projected to shorten over time, decreasing to 127, 126, 126, and 124 days in the 2040s and further to 124, 119, 114, and 110 days by the 2080s under SSP126 to SSP585. On average across the three sites, it was expected to decline to 126 days in the 2040s (11 days shorter than the baseline) and to 117 days in the 2080s (a decrease of 20 days).

3.4. Simulated sugarcane yield changes

The projected yield change, including changes in FW, above-ground biomass dry weight (DW), and SW, showed a consistent increasing trend across all climate change scenarios in the three study sites (Fig. 5). A modest yield increase was projected by the 2040s, followed by a more pronounced rise by the 2080s as emissions increased. Notably, under SSP126, yield changes between the 2040s and 2080s were minimal, suggesting a limited impact under lower emission pathways. From SSP126 to SSP585, FW was projected to increase from 6 to 34 Mg ha^{-1} (i.e., 6–29 %), DW from 2 to 11 Mg ha^{-1} (6–29 %), and SW from 1 to 7 Mg ha^{-1} (10–46 %) across the three study sites. The largest absolute increases in FW, DW, and SW were projected at Broadwater under SSP585 in the 2080s, whereas the smallest absolute increases were observed at Harwood under SSP126 in the same period. However, Harwood was projected to experience the highest percentage increases in FW, DW, and SW under SSP585 in the 2080s, highlighting the varying site-specific responses to climate change scenarios.

3.5. Projected change in the annual harvest frequency

During the baseline period (1981–2020), the annual harvest frequency was 80 %, 70 %, and 50 % for Condong, Broadwater, and Harwood, respectively (Fig. 6). In future projections, the annual harvest frequency was projected to increase with rising emissions, with a slight rise expected by the 2040s, followed by a more pronounced increase by the 2080s. In the 2040s, the annual harvest frequency ranged from 90 % to 91 % in Condong, 89 % to 90 % in Broadwater, and 70 % to 73 % in Harwood across the four scenarios. By the 2080s, it ranged from 90 % to 94 % in Condong, 88 % to 96 % in Broadwater, and 68 % to 85 % in Harwood across the four scenarios. Additionally, the greatest incremental changes in annual harvest frequency were observed under SSP585 in the 2080s across all three sites, with increments of 14 % at Condong, 26 % at Broadwater, and 35 % at Harwood. This pattern showed a rising trend in the incremental change of annual harvest frequency from the cooler region of Harwood to the warmer region of Condong.

3.6. Statistical analysis of factors influencing yield changes

The regression model quantified the contribution of each climate variable to yield changes in stalk fresh weight (ΔFW), above-ground biomass dry weight (ΔDW), and sucrose weight (ΔSW), explaining 93–96 % of the total variation in yield (Table 2). This indicated a strong

Table 2
Regression coefficients for projected changes in yield (ΔY) in response to changes in temperature (ΔT), rainfall (ΔRf), global solar radiation (ΔRad), and CO_2 concentration (ΔCO_2) at three sites. FW, DW, and SW represent sugarcane stalk fresh weight, above-ground biomass dry weight, and sucrose weight, respectively. *, ** and *** indicate the significant at the level of $P < 0.05$, $P < 0.01$ and $P < 0.001$, respectively.

ΔY	Site	*a* (ΔT) (kg ha^{-1} °C^{-1})	*b* (ΔRf) (kg ha^{-1} mm^{-1} yr^{-1})	*c* (ΔCO_2) (kg ha^{-1} ppm^{-1})	*d* (ΔRad) (kg ha^{-1} (MJ m^{-2} yr^{-1})$^{-1}$)	R^2	Partial R^2			
							ΔT	ΔRf	ΔCO_2	ΔRad
ΔFW	Condong	2875***	16.99***	46.09***	0.95	0.95	0.29	0.20	0.48	0.00
	Broadwater	2936***	15.13***	48.83***	2.10	0.95	0.30	0.11	0.45	0.00
	Harwood	2190***	26.91***	39.96***	4.34**	0.96	0.36	0.43	0.51	0.04
ΔDW	Condong	828***	5.51***	17.12***	0.21	0.93	0.18	0.15	0.45	0.00
	Broadwater	916***	4.94***	18.17***	1.30	0.94	0.21	0.07	0.42	0.01
	Harwood	432***	8.93***	17.34***	2.39***	0.95	0.13	0.36	0.57	0.09
ΔSW	Condong	619***	3.43***	10.55***	0.70	0.94	0.27	0.17	0.48	0.01
	Broadwater	669***	2.37***	10.08***	0.81	0.95	0.31	0.05	0.41	0.01
	Harwood	466***	5.01***	8.68***	1.20***	0.95	0.31	0.31	0.46	0.06

relationship between changes in climatic factors and sugarcane yield across the three sites. All climatic factors had a positive effect on yield changes, and temperature change (ΔT), rainfall change (ΔRf), and CO_2 concentration change (ΔCO_2) significantly influenced yield variation ($p < 0.001$) at all sites. Among the climate variables, ΔCO_2 accounted for the largest proportion of yield variation, with partial R^2 values ranging from 0.41 to 0.57 across the three sites. However, the second most influential factor varied by location, with ΔT having a stronger influence at Condong and Broadwater, whereas ΔRf was more influential at Harwood.

The site-specific responses further illustrate this variation. Broadwater exhibited the highest sensitivity to ΔT among the three sites, with ΔFW, ΔDW, and ΔSW increasing by 2936, 916, and 669 kg ha^{-1} °C^{-1}, respectively. In contrast, Harwood showed the strongest response to ΔRf, with corresponding increases of 26.91, 8.93, and 5.01 kg ha^{-1} per mm of rainfall. The effect of ΔCO_2 was relatively consistent across sites, contributing average increases of 45, 18, and 10 kg ha^{-1} in FW, DW, and SW, respectively, for each ppm increase in atmospheric CO_2.

4. Discussion

This study provides valuable insights into the potential impacts of climate change on sugarcane yield and harvest frequency. However, it is important to acknowledge the uncertainties and limitations of the modeling approach (Corbeels et al., 2018; Jaiswal et al., 2023; Wang et al., 2024). First, the simulations assume optimal conditions, excluding biotic stresses (e.g., pests and diseases) and abiotic stresses beyond those represented by climatic variables (e.g., extreme weather events such as heatwaves or flooding). In reality, these factors can significantly affect sugarcane growth and yield, particularly under changing climate conditions (Hussain et al., 2018; Zhao and Li, 2015), and their exclusion may contribute to an overestimation of future yield potential. Additionally, while the QCANE model has been previously validated for sugarcane yield in various regions, including Queensland and international locations, we acknowledge that in this study, model validation focused primarily on yield-related outputs. The absence of validation for other key outputs such as phenological markers and water flux variables (e.g., evapotranspiration, soil moisture) represents a limitation. Future work should aim to expand model evaluation to include water balance components and other key processes of sugarcane growth, to enhance confidence in the simulation of sugarcane productivity under climate change.

Second, a uniform harvest date was assumed for each region, whereas actual harvest seasons span several months to align with milling capacity. This approach simplifies operational variability and may not fully capture regional practices. Finally, our simulations relied on a validated crop model (QCANE), climate projections from 27 GCMs under CMIP6, and the assumption that current management practices remained unchanged throughout the 21st century. These projections inherently involve uncertainty, as Corbeels et al. (2018) emphasized that GCMs are designed to explore potential future climate trends rather than provide precise predictions and assuming fixed management may not reflect future realities. Therefore, while the projections indicated promising opportunities for more frequent annual harvesting under warming conditions, these findings should be interpreted within the bounds of these uncertainties. However, the decision to hold management practices constant was made to intentionally isolate the effects of climate change on sugarcane yield and harvest frequency, allowing for a clearer attribution of yield changes to climatic drivers. This study provides a well-defined, climate-driven baseline, and future studies are encouraged to incorporate potential future farming strategies to enhance the robustness and policy relevance of long-term projections. Additionally, future research could explore regional variations in climate sensitivity, projected yield impacts, and adaptive management strategies across Australia's broader sugarcane-growing regions.

The performance of the QCANE model was validated by comparing simulated and observed values for stalk fresh weight (FW) and sucrose weight (SW), showing strong agreement across the study regions. Similar results were observed in the study by Zu et al. (2018), which indicated the accuracy of the QCANE model in simulating sugarcane yields across diverse growth conditions in southern China. While phenological stages were not explicitly validated at the study sites, the QCANE model has shown strong performance in simulating sugarcane growth and development. Using data from Bundaberg, Queensland (24.83°S, 152.43°E), the simulated time series of stalk fresh weight, above-ground dry matter, and sucrose weight showed strong agreement with observations across crop growth, achieving performance efficiency values between 0.81 and 0.98 (see Supplementary materials, Fig. S8). Although this did not directly validate phenological stages, it provides strong evidence of the model's high accuracy in simulating growth dynamics. Additionally, Zu et al. (2018) reported excellent agreement for phenological development stages in China, with R^2 of 0.99 for both simulated versus observed emergence days and cane appearance days. These findings support confidence in the model's ability to simulate key physiological processes relevant to this study.

Our analysis indicated a sustained warming trend projected for sugarcane-growing regions in northern coastal NSW over the coming decades based on multi-model mean outputs from 27 CMIP6 GCMs. In contrast, projections for annual rainfall showed considerable uncertainty among the GCMs, as indicated by the wide interdecile (Q90 – Q10) range of projected changes, spanning both decreases and increases. For example, under SSP585 in the 2080s at Condong, the Q90 – Q10 range extended from −285 mm to 281 mm across the 27 GCMs. These projected trends in temperature and rainfall align with findings from previous studies in Australia that utilized both global and regional climate models (AdaptNSW, 2024a; Nishant et al., 2021; Wang et al., 2018; Wang et al., 2022).

The QCANE model simulates phenology based on the accumulation of thermal time, accounting for the temperature effects in both suboptimum and supra-optimum regions (Liu et al., 1998). In this study, the results indicated that phenological stages, such as emergence and cane appearance, shortened under future scenarios. By the 2080s, the emergence stage was projected to shorten by 7 days, averaging 19 days, while the cane appearance stage was expected to decrease by 20 days, reaching 117 days. This reduction was primarily due to elevated temperatures accelerating plant development by increasing the rate of thermal time accumulation, thereby advancing the onset of various phenological phases (He et al., 2015; Jones and Singels, 2018; Sparks et al., 2000). These findings were consistent with previous studies, where Jaiswal et al. (2023) reported that the average duration from planting to emergence was shortened by up to 14.5 days under a high-emission pathway by 2070–2099 in India using the CANEGRO model. Similarly, Ruan et al. (2018) simulated that the duration from planting or ratooning to cane appearance decreased by up to 20 days during the 2090s in southern China using the APSIM-Sugarcane model.

Our simulations projected that sugarcane yield would increase across the three study sites in the future, with the highest increases in FW, DW, and SW occurring at Broadwater under SSP585 by the 2080s, reaching up to 34 Mg ha^{-1}, 11 Mg ha^{-1}, and 7 Mg ha^{-1}, respectively. Statistical analysis demonstrated that changes in future climatic factors contributed positively to yield increases, with temperature, rainfall, and CO_2 concentration significantly influencing yield variation across all sites. Among the climatic factors, changes in [CO_2] explained the largest proportion of yield variation with the highest partial R^2 values across the three sites, highlighting its dominant role in driving yield responses under future climate conditions. Following [CO_2], temperature was the second influential factor in Condong and Broadwater, however, rainfall was more influential at Harwood. This site-specific variation likely reflects differences in baseline climate and water availability. Condong and Broadwater, located in more humid regions, typically receive higher annual rainfall, which may reduce the limiting role of water, making temperature a more critical factor influencing growth and development.

In contrast, Harwood experiences relatively lower rainfall and is more prone to water stress, making yield more sensitive to variations in rainfall. These findings align with previous studies, which indicate that temperature drives yield variability in wetter environments (Muchow et al., 1996), while rainfall is the dominant constraint in drier or more variable regions (Everingham et al., 2015).

However, radiation was not a significant factor influencing yield. The non-significant effect of solar radiation may be attributed to its relatively small projected change (−2 % to 4 %, as shown in Fig. 3) compared to other variables such as rainfall, which ranges from −17 % to 17 %. This limited variability reduces its statistical influence in the linear regression analysis. Similarly, Ruan et al. (2018) found that solar radiation had limited impact on stalk fresh weight and dry biomass under future climate scenarios in China. Furthermore, Australia has the highest average solar radiation per square metre of any continent in the world (ARENA, 2013). As a result, solar radiation is generally abundant and rarely serves as a growth-limiting factor for crops and vegetation compared to other climatic drivers such as water availability and temperature. For example, Wang et al. (2022) assessed the impacts of climate change on aboveground biomass in regenerating native forests in southeast Australia and found that solar radiation had a relatively minor effect on biomass accumulation.

Elevated [CO_2] levels associated with climate change can enhance sugarcane growth through the CO_2 fertilization effect (Vu et al., 2006). Higher [CO_2] is likely to have a significant impact on sugarcane photosynthesis, enabling the plant to partially close its stomata without substantially reducing CO_2 uptake (De Souza et al., 2008; Reddy and Hodges, 2000). De Souza et al. (2008) demonstrated that sugarcane exposed to double the normal [CO_2] levels experienced a 30 % increase in photosynthesis and accumulated 40 % more biomass compared to plants grown under normal [CO_2] conditions in Brazil. Similarly, in Australia, simulations by Biggs et al. (2013) showed that sugarcane yields were substantially influenced by the CO_2 fertilization effect, with yields 10–14 % higher than identical scenarios without the CO_2 effect. In addition, under projected rainfall decline, rising [CO_2] levels can improve water use efficiency by reducing stomatal conductance and transpiration, thereby minimizing water loss (Jackson et al., 2016; Malan, 2017). Although higher temperatures can increase transpiration (Singels et al., 2014), the CO_2 fertilization effect helps offset this increase (Marin et al., 2013), thereby contributing to the sustainability of sugarcane production under future climate conditions.

Future climate projections and impact analyses are important to assess the potentially changing sugarcane harvest frequency under climate change. To our knowledge, this is the first study that projected the effects of climate change on harvest frequency in Australia. In NSW, the annual harvest frequency was projected to increase, with 68–96 % of years in the future expected to support annual harvests (Fig. 6). This shift could significantly increase the yield for all sites as the cumulative yield of 1-year-old sugarcane was higher than that of 2-year-old sugarcane within two years (Fig. S9, see Supplementary materials). The lower average yield over a 2-year growth cycle resulted from the inclusion of a suboptimal yielding year, often caused by unfavorable climate conditions that extend the crop cycle into a second year. In addition, the lower yields in 2-year-old sugarcane were attributed to the reduced growth phenomenon (RGP) commonly reported in NSW (Muchow et al., 1999; Park et al., 2005; Sage et al., 2013). In the second year, greater biomass accumulation leads to increased respiration losses, substantially slowing the rate of further biomass production. Therefore, the average yield of the 2-year-old sugarcane was lower when compared to the yield of two consecutive 1-year cycles for the same years (Fig. S9, see Supplementary materials). Despite this, 2-year cultivation may still be necessary if first-year yields are unsatisfactory for some regions. This decision is often driven by economic considerations, including the costs of harvesting and transportation, as well as potential losses during sugar milling, which may outweigh the benefits of harvesting twice within a two-year period (SunshineSugar, 2022).

Increased yield and more frequent annual harvests suggest that climate change could positively impact sugarcane production in NSW, offering opportunities to enhance future productivity. Warmer temperatures could enable the expansion of cultivation into cooler southern regions, which are expected to become favorable for sugarcane growth. Additionally, shorter growing seasons will drive the development of a more efficient sugarcane industry. To fully capitalize on these opportunities, the economic feasibility of shifting to more frequent annual harvesting should be comprehensively evaluated by weighing the yield benefits against the required investments in mechanization, transportation, and processing infrastructure. Additionally, it will be essential to develop new sugarcane cultivars that are better adapted to changing climatic conditions (Scortecci et al., 2012; Srivastava and Rai, 2012). High-yielding, fast-growing varieties with enhanced photosynthesis optimized for 1-year growth cycles, will be critical for maximizing productivity during shorter growing periods. These implications would be crucial for developing adaptive strategies and informing policymakers to make evidence-based decisions that support the sustainability of the sugarcane industry in NSW under climate change.

5. Conclusion

This study evaluated the potential impacts of climate change on sugarcane yield and the annual harvest frequency using 27GCMs under four scenarios (SSP126, SSP245, SSP370, and SSP585) in northern coastal NSW. Our findings indicated that climate change was projected to positively affect sugarcane yield, accompanied by accelerated crop growth. Among climatic factors, temperature, rainfall, and [CO_2] had significant effects on yield. Furthermore, future projections indicated an increase in annual harvest frequency, with a particularly pronounced rise in the cooler region of Harwood. The shift toward 1-year harvest was expected to boost sugarcane productivity in NSW. These findings provide valuable insights for leveraging the benefits of climate change in the sugarcane industry and contribute to the development of sustainable practices and more efficient production management strategies in NSW, ensuring the resilience and long-term sustainability of sugarcane cultivation under changing climatic conditions.

CRediT authorship contribution statement

Shijin Yao: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **De Li Liu:** Writing – review & editing, Software, Methodology, Data curation, Conceptualization. **Bin Wang:** Writing – review & editing, Methodology, Formal analysis, Conceptualization. **Jonathan Kennedy Webb:** Writing – review & editing, Supervision, Methodology. **Siyi Li:** Writing – review & editing, Methodology. **Alfredo Huete:** Writing – review & editing. **Keyu Xiang:** Software. **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.

Acknowledgements

The first author acknowledges the China Scholarship Council (CSC No. 202008410239) for financial support during her Ph.D. studies. Facilities for conducting this study were provided by the New South Wales Department of Primary Industries.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2025.104502.

Data availability

Data will be made available on request.

References

AdaptNSW, 2024a. Climate Change in NSW. https://www.climatechange.environment.nsw.gov.au/my-region/nsw.

AdaptNSW, 2024b. Interactive Climate Change Projections Map. https://www.climatechange.environment.nsw.gov.au/projections-map.

ARENA, 2013. Australian Energy Resource Assessment. https://arena.gov.au/assets/2013/08/Chapter-10-Solar-Energy.pdf.

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.

Bonnett, G., Hewitt, M., Glassop, D., 2006. Effects of high temperature on the growth and composition of sugarcane internodes. Aust. J. Agric. Res. 57, 1087–1095.

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.

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.

Dias, H.B., Inman-Bamber, G., 2020. Sugarcane: contribution of process-based models for understanding and mitigating impacts of climate variability and change on production. Syst. Model. 217–260.

dos Santos Vianna, M., Nassif, D.S.P., dos Santos Carvalho, K., Marin, F.R., 2020. Modelling the trash blanket effect on sugarcane growth and water use. Comput. Electron. Agric. 172, 105361.

dos Santos Vianna, M., Metselaar, K., van Lier, Q.D.J., Gaiser, T., Marin, F.R., 2024. The importance of model structure and soil data detail on the simulations of crop growth and water use: a case study for sugarcane. Agric. Water Manag. 301, 108938.

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.

FAOSTAT, 2023. Food & Agriculture Data-Crops and Livestock Products. https://www.fao.org/faostat/en/#data/QCL.

Feng, P., Wang, B., Liu, D.L., Xing, H., Ji, F., Macadam, I., Ruan, H., Yu, Q., 2018. Impacts of rainfall extremes on wheat yield in semi-arid cropping systems in eastern Australia. Clim. Chang. 147, 555–569.

Guga, S., Ma, Y., Riao, D., Zhi, F., Xu, J., Zhang, J., 2023. Drought monitoring of sugarcane and dynamic variation characteristics under global warming: a case study of Guangxi, China. Agric. Water Manag. 275, 108035.

Haerter, J., Hagemann, S., Moseley, C., Piani, C., 2011. Climate model bias correction and the role of timescales. Hydrol. Earth Syst. Sci. 15, 1065–1079.

He, L., Asseng, S., Zhao, G., Wu, D., Yang, X., Zhuang, W., Jin, N., Yu, Q., 2015. Impacts of recent climate warming, cultivar changes, and crop management on winter wheat phenology across the Loess Plateau of China. Agric. For. Meteorol. 200, 135–143.

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. IntechOpen.

Inman-Bamber, N., 1991. A growth model for sugar-cane based on a simple carbon balance and the CERES-Maize water balance. S. Afr. J. Plant Soil 8, 93–99.

Inman-Bamber, N., Culverwell, T., McGlinchey, M., 1993. Predicting yield responses to irrigation of sugarcane from a growth model and field records. In: Proceedings of the South African Sugar Technologists' Association. Citeseer, pp. 66–72.

IPCC, 2021. Climate change 2021: the physical science basis. In: Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. https://www.ipcc.ch/report/ar6/wg1/.

Jackson, P., Hale, A., Bonnett, G., Lakshmanan, P., 2014. Sugarcane. In: Alien Gene Transfer in Crop Plants, Vol. 2. Achievements and Impacts, pp. 317–345.

Jackson, P., Basnayake, J., Inman-Bamber, G., Lakshmanan, P., Natarajan, S., Stokes, C., 2016. Genetic variation in transpiration efficiency and relationships between whole plant and leaf gas exchange measurements in Saccharum spp. and related germplasm. J. Exp. Bot. 67, 861–871.

Jaiswal, R., Mall, R.K., Patel, S., Singh, N., Mendiratta, N., Gupta, A., 2023. Indian sugarcane under warming climate: a simulation study. Eur. J. Agron. 144.

Jeffrey, S.J., Carter, J.O., Moodie, K.B., Beswick, A.R., 2001. Using spatial interpolation to construct a comprehensive archive of Australian climate data. Environ. Model. Softw. 16, 309–330.

Jones, M.R., Singels, A., 2018. Refining the Canegro model for improved simulation of climate change impacts on sugarcane. Eur. J. Agron. 100, 76–86.

Jones, M., Singels, A., Inman-Banber, N., 2011. Simulating source and sink control of structural growth and development and sugar accumulation in sugarcane. Proc. South Afr. Sugarcane Technol. Assoc. 84, 157–163.

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.

Keating, B., Robertson, M., Muchow, R., Huth, N., 1999. Modelling sugarcane production systems I. Development and performance of the sugarcane module. Field Crop Res. 61, 253–271.

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, L., Wang, B., Feng, P., Liu, D.L., He, Q., Zhang, Y., Wang, Y., Li, S., Lu, X., Yue, C., Li, Y., He, J., Feng, H., Yang, G., Yu, Q., 2022. Developing machine learning models with multi-source environmental data to predict wheat yield in China. Comput. Electron. Agric. 194.

Liu, D.L., 1996. Incorporating diurnal light variation and canopy light attenuation into analytical equations for calculating daily gross photosynthesis. Ecol. Model. 93, 175–189.

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., Helyar, K., 2003. Simulation of seasonal stalk water content and fresh weight yield of sugarcane. Field Crop Res. 82, 59–73.

Liu, D.L., Kingston, G., 1995. QCANE: A Simulation Model of Sugarcane Growth and Sugar Accumulation. Research and Modelling Approaches to Assess Sugarcane Production Opportunities and Constrains. University of Queensland, St. Lucia, pp. 25–29.

Liu, D.L., Zuo, H., 2012. Statistical downscaling of daily climate variables for climate change impact assessment over New South Wales, Australia. Clim. Chang. 115, 629–666.

Liu, D.L., Kingston, G., Bull, T., 1998. A new technique for determining the thermal parameters of phenological development in sugarcane, including suboptimum and supra-optimum temperature regimes. Agric. For. Meteorol. 90, 119–139.

Liu, D.L., Zeleke, K.T., Wang, B., Macadam, I., Scott, F., Martin, R.J., 2017. Crop residue incorporation can mitigate negative climate change impacts on crop yield and improve water use efficiency in a semiarid environment. Eur. J. Agron. 85, 51–68.

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.

Malan, C., 2017. Influence of Elevated CO_2 on the Growth, Yield and Photosynthesis of Sugarcane. North-West University (South Africa).

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., Jones, J.W., Singels, A., Royce, F., Assad, E.D., Pellegrino, G.Q., Justino, F., 2013. Climate change impacts on sugarcane attainable yield in southern Brazil. Clim. Chang. 117, 227–239.

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.

Marin, F., Jones, J.W., Boote, K.J., 2017. A stochastic method for crop models: including uncertainty in a sugarcane model. Agron. J. 109, 483–495.

Marin, F.R., Gonçalves, I.Z., Meza, F.J., Néstor, M., Riaño, H., Peña, Q.A.J., Heinneman, A.B., Streck, N.A., Alencar Jr., Z., Vianna, M.S., 2023. Modeling the Impact of Climate Change on Agriculture in Latin America.

Muchow, R., Robertson, M., Keating, B., 1996. Limits to the Australian Sugar Industry: Climatic and Biological Factors, Intensive Sugarcane Production: Meeting the Challenges beyond 2000. CSIRO Tropical Agriculture and CRC for Sustainable Sugar Production, Brisbane, Australia, pp. 37–54.

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 Reports Schedules 27, CTA012.

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.

O'Neill, B.C., Tebaldi, C., Van Vuuren, D.P., Eyring, V., Friedlingstein, P., Hurtt, G., Knutti, R., Kriegler, E., Lamarque, J.-F., Lowe, J., 2016. The scenario model intercomparison project (ScenarioMIP) for CMIP6. Geosci. Model Dev. 9, 3461–3482.

Park, S., Robertson, M., Inman-Bamber, N., 2005. Decline in the growth of a sugarcane crop with age under high input conditions. Field Crop Res. 92, 305–320.

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.

Reddy, K.R., Hodges, H.F., 2000. Climate Change and Global Crop Productivity. CABI, Wallingford, UK.

Reyenga, P.J., Howden, S.M., Meinke, H., McKeon, G.M., 1999. Modelling global change impacts on wheat cropping in South-East Queensland, Australia. Environ. Model. Softw. 14, 297–306.

Richardson, C., Wright, D., 1984. WGEN: A model for generating daily weather variables. In: ARS-8. US Department of Agriculture, Agricultural Research Service, Washington, DC, p. 83.

Ruan, H., Feng, P., Wang, B., Xing, H., O'Leary, G.J., Huang, Z., Guo, H., Liu, D.L., 2018. Future climate change projects positive impacts on sugarcane productivity in southern China. Eur. J. Agron. 96, 108–119.

Sage, R.F., Peixoto, M.M., Sage, T.L., 2013. Photosynthesis in sugarcane. In: Sugarcane: Physiology, Biochemistry, and Functional Biology, pp. 121–154.

Sanches, G.M., Bordonal, R.D.O., Magalhães, P.S.G., Otto, R., Chagas, M.F., Cardoso, T.D. F., Luciano, A.C.D.S., 2023. Towards greater sustainability of sugarcane production by precision agriculture to meet ethanol demands in south-Central Brazil based on a life cycle assessment. Biosyst. Eng. 229, 57–68.

Scortecci, K.C., Creste, S., Calsa Jr., T., Xavier, M.A., Landell, M.G., Figueira, A., Benedito, V.A., 2012. Challenges, opportunities and recent advances in sugarcane breeding. Plant Breed. 1, 267–296.

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.

Singels, A., Jones, M., van Den Berg, M., 2008. DSSAT v4. 5-canegro sugarcane plant module. South African Sugarcane Research Institute.

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.

Sparks, T., Jeffree, E., Jeffree, C., 2000. An examination of the relationship between flowering times and temperature at the national scale using long-term phenological records from the UK. Int. J. Biometeorol. 44, 82–87.

SRA, 2024. Variety Guide. https://sugarresearch.com.au/growers-and-millers/varieties/.

Srivastava, A.K., Rai, M.K., 2012. Sugarcane production: impact of climate change and its mitigation. Biodivers. J. Biol. Divers. 13, 214–227.

SunshineSugar, 2022. Reference Notes for New Cane Growers in NSW. https://www.sunshinesugar.com.au/wp-content/uploads/2022/01/Reference-notes-NSW-New-Growers-2022_.pdf.

Thornley, J.H., Johnson, I.R., 1990. Plant and Crop Modelling. Clarendon Oxford.

Topp, V., Litchfield, F., Coelli, R., Ashton, D., 2022. Financial Performance of Sugarcane Farms 2020–21 to 2021–22. ABARES, Canberra. December. https://www.agriculture.gov.au/abares/research-topics/surveys/sugar#download.

USDA, 2022. Sugar: World Markets and Trade. https://apps.fas.usda.gov/psdonline/circulars/sugar.pdf.

USDA, 2023. Sugar Annual. https://apps.fas.usda.gov/newgainapi/api/Report/DownloadReportByFileName?fileName=Sugar+Annual_Canberra_Australia_AS2022-0009.pdf.

van Heerden, P.D., Donaldson, R.A., Watt, D.A., Singels, A., 2010. Biomass accumulation in sugarcane: unravelling the factors underpinning reduced growth phenomena. J. Exp. Bot. 61, 2877–2887.

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.

Wang, B., Liu, D.L., O'Leary, G.J., Asseng, S., Macadam, I., Lines-Kelly, R., Yang, X., Clark, A., Crean, J., Sides, T., 2018. Australian wheat production expected to decrease by the late 21st century. Glob. Chang. Biol. 24, 2403–2415.

Wang, B., Waters, C., Anwar, M.R., Cowie, A., Liu, D.L., Summers, D., Paul, K., Feng, P., 2022. Future climate impacts on forest growth and implications for carbon sequestration through reforestation in Southeast Australia. J. Environ. Manag. 302, 113964.

Wang, B., Jägermeyr, J., O'Leary, G.J., Wallach, D., Ruane, A.C., Feng, P., Li, L., Liu, D. L., Waters, C., Yu, Q., 2024. Pathways to identify and reduce uncertainties in agricultural climate impact assessments. Nat. Food 5, 550–556.

Wegener, M., Jones, C., Russell, J., 1988. Simulating cane growth under Australian conditions. In: Proc. Aust. Soc. Sugar Cane Technol, pp. 99–106.

Wei, X., Eglinton, J., Piperidis, G., Atkin, F., Morgan, T., Parfitt, R., Hu, F., 2022. Sugarcane breeding in Australia. Sugar Tech. 24, 151–165.

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.

Yao, S., Wang, B., Li Liu, D., Li, S., Ruan, H., Yu, Q., 2025. Assessing the impact of climate variability on Australia's sugarcane yield in 1980–2022. Eur. J. Agron. 164, 127519.

Zhang, X.-C., 2005. Spatial downscaling of global climate model output for site-specific assessment of crop production and soil erosion. Agric. For. Meteorol. 135, 215–229.

Zhang, X., 2007. A comparison of explicit and implicit spatial downscaling of GCM output for soil erosion and crop production assessments. Clim. Chang. 84, 337–363.

Zhao, D., Li, Y.-R., 2015. Climate change and sugarcane production: potentialimpact and mitigation strategies. Int. J. Agron. 2015, 1–10.

Zhu, X., Dong, H., Li, Q., Qiu, X., Sun, Y., 2024. Sugarcane water requirement and yield projections in major producing regions of China under future climate scenarios. Theor. Appl. Climatol. 155, 2729–2745.

Zu, Q., Mi, C., Liu, D.L., He, L., Kuang, Z., Fang, Q., Ramp, D., Li, L., Wang, B., Chen, Y., 2018. Spatio-temporal distribution of sugarcane potential yields and yield gaps in Southern China. Eur. J. Agron. 92, 72–83.