

RESEARCH ARTICLE

# Sensitivity Analysis of the APSIM-Sugar and CANEGRO Sugarcane Growth Simulation Models

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## Abstract

This study investigates the sensitivity of the APSIM and CANEGRO crop models to key climatic parameters and genetic coefficients in simulating sugarcane growth and yield. Sensitivity analyses to genetic coefficient identified critical genetic parameters influencing crop performance. In the CANEGRO model, MaxPARCE, APFMX, and STKPFMAX were the most influential for yield, biomass, and sucrose content, while LFMAX and SER0 significantly impacted LAI and stalk height. These findings suggest that calibration efforts should prioritize phenological, growth, and yield-related parameters. In contrast, global sensitivity analysis using the APSIM model highlighted RUE4, MSS, and GLN as the most impactful parameters affecting cane yield, commercial cane sugar (CCS), and sucrose accumulation, with RUE and MSS emerging as key contributors to both biomass production and sugar content. Additionally, both models exhibited sensitivity to climatic variables. A rise in temperature resulted in a decline in cane yield, more pronounced in CANEGRO (31.35% reduction at +6 °C) compared to APSIM (15.81%). Increases in solar radiation enhanced cane yield and sucrose dry mass, while reduced radiation had adverse effects. Overall, the findings provide actionable insights for improving model calibration and support cultivar selection and management practices under projected climate change scenarios.

**Keywords:** APSIM; Crop Modelling; CANEGRO; Sensitivity Analysis; Genetic Coefficient

## 1. Introduction

The CANEGRO model simulates sugarcane growth using a source–sink approach, where stalk volume reflects sink strength. Canopy development is driven by energy balance, and intercepted radiation powers photosynthesis. Biomass is allocated to different plant parts based on growth stage, temperature, and water stress, with stalk partitioning modelled through a nonlinear function influenced by environmental conditions (Singh *et al.*, 2010). It has been used to study phenology, yield variability (Inman-Bamber, 1991), regional productivity (Inman-Bamber *et al.*, 1998), and bioenergy potential (Jones *et al.*, 2006). Similarly, APSIM-Sugar is a process-based model tailored for

sugarcane, integrating climate, soil, and crop physiology to evaluate yield, water use, and nutrient dynamics (Keating *et al.*, 1999). It aids in optimizing agronomic practices and assessing sustainability under varying conditions (Singels *et al.*, 2008; Robertson *et al.*, 2017).

Sensitivity analysis in crop simulation modeling refers to the evaluation of how changes in input variables—such as genetic coefficients, temperature, rainfall, fertilizer, or atmospheric CO<sub>2</sub>—affect the output, typically crop yield. It helps in understanding model behaviour under varying conditions, identifying influential factors, and guiding model calibration and decision-making. Local sensitivity analysis assesses how

small changes in a single parameter, while keeping others fixed, affect model output, but it ignores interactions and broader parameter ranges. In contrast, global sensitivity analysis evaluates the impact of all parameters across their full range, considering interactions for a more comprehensive assessment.

This study has performed a local sensitivity analysis of meaningful genetic parameters in CANEGRO model and a global sensitivity analysis of APSIM-Sugar model to determine the important parameters which are critical to calibration of both the models for simulating growth and yield of sugarcane. Additionally, both models were tested for sensitivity to major climatic drivers—temperature and solar radiation—to assess their responses under potential climate change scenarios.

Overall, sensitivity analysis aids in prioritizing parameters, reducing uncertainty, guiding data collection, and improving cultivar selection and management strategies. This enhances the robustness and practical utility of crop models for predicting sugarcane yield across varying environmental and agronomic conditions.

## 2. Materials and Methodology

### 2.1 Sensitivity analysis of DSSAT CANEGRO and APSIM sugar model

Sensitivity analysis was conducted to examine how the model responds to variations in input parameters. A model is considered sensitive to a specific input parameter if small changes in its value result in significant changes in the model's output. In this study, two types of sensitivity analyses were performed: (i) genetic coefficients of the cultivar, which focused on understanding the impact of cultivar-specific parameters (e.g., phenology, growth, and yield attributes) on model outputs, are critical for accurate model calibration and (ii) changes in climatic parameters, which assessed the model's response to variations in key climate variables such as temperature, rainfall, solar radiation, and CO<sub>2</sub> concentration.

The workflow of sensitivity analysis of genetic coefficients is illustrated in the Figure 1 and Figure 2, which outlines the systematic steps followed to evaluate the sensitivity of key genetic parameters on model outputs. The lower and upper bounds of genetic coefficients for the APSIM and CANEGRO models, which represent the range of variation for each parameter, are provided in Table 1 and Table 2, respectively.

### 2.2 Sensitivity analysis of climatic parameters

The sensitivity of the models to climatic parameters

was assessed using the "Environmental Modification" feature in the DSSAT-CANEGRO model and the "Climate Controller" tool in the APSIM Sugar model. Simulations involved varying average temperatures from -2°C to +6°C, while rainfall was adjusted between -100% and +40% variation in the APSIM Sugar model. Solar radiation was modified by -25% to +25% in APSIM Sugar and by -5 to +5 MJ/m<sup>2</sup>/day in DSSAT-CANEGRO. Additionally, atmospheric CO<sub>2</sub> concentrations were varied within a range of -150 to +150 ppm in DSSAT-CANEGRO. The sensitivity analysis specifically focused on cane yield (t/ha) and sucrose dry mass (t/ha), providing valuable insights into how changes in environmental parameters affect these critical performance indicators.

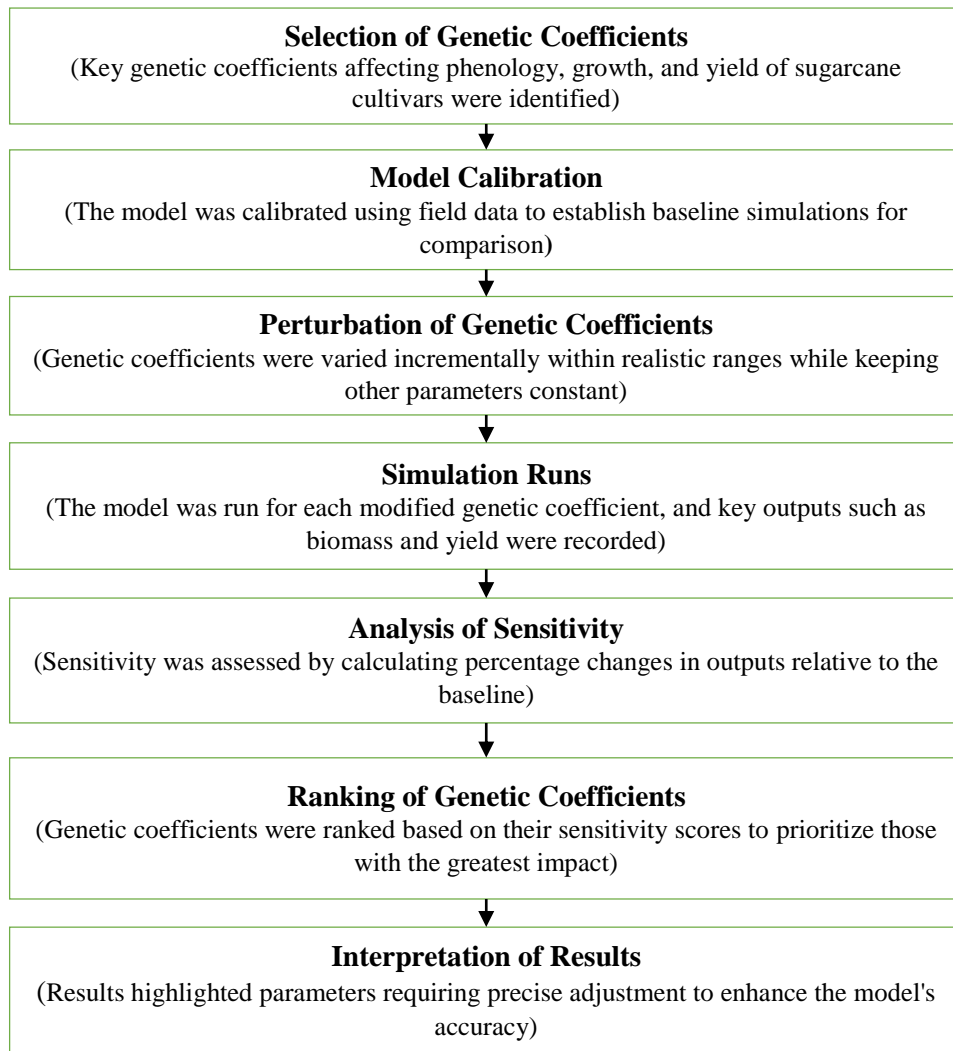
## 3. Results and Discussion

### 3.1 Local sensitivity analysis of genetic coefficients in the CANEGRO model

Figure 3 illustrates the effect of increasing the genetic coefficient parameter values of sugarcane cultivars on cane yield, while Figure 4 depicts the impact of parameter increments on aerial dry biomass and sucrose percentage.

#### 3.1.1 Sensitivity analysis of genetic coefficients for cane yield (t/ha)

Among the tested genetic coefficients, MaxPARCE emerged as the most influential parameter affecting cane yield, with a Sensitivity Index (SI) of 1.56, ranking first (Figure 6). This parameter determines the plant's capacity to convert intercepted Photosynthetically Active Radiation (PAR) into assimilates (g MJ<sup>-1</sup>). A higher MaxPARCE enhances biomass accumulation through increased photosynthetic efficiency, ultimately boosting cane yield. The second most sensitive parameter was STKPFMAX (SI = 1.07), which governs the maximum proportion of dry mass that can be allocated to stalks. This influences the stalk size and contributes directly to yield formation under high-temperature conditions. The phenological parameter PII (Phyllochron Interval 1), with an SI of -0.563, was the third most sensitive. Its negative value indicates that increasing PII results in a decrease in cane yield, likely due to reduced early leaf formation and, subsequently, lower photosynthetic capacity. Lastly, APFMX (SI = 0.33) ranked fourth. This parameter affects the fraction of biomass allocated to aerial components, thus influencing vegetative growth and yield. These findings are in line with Coelho *et al.*, (2019), who also reported PARCEmax and STKPFmax as highly sensitive in stalk dry weight simulations.



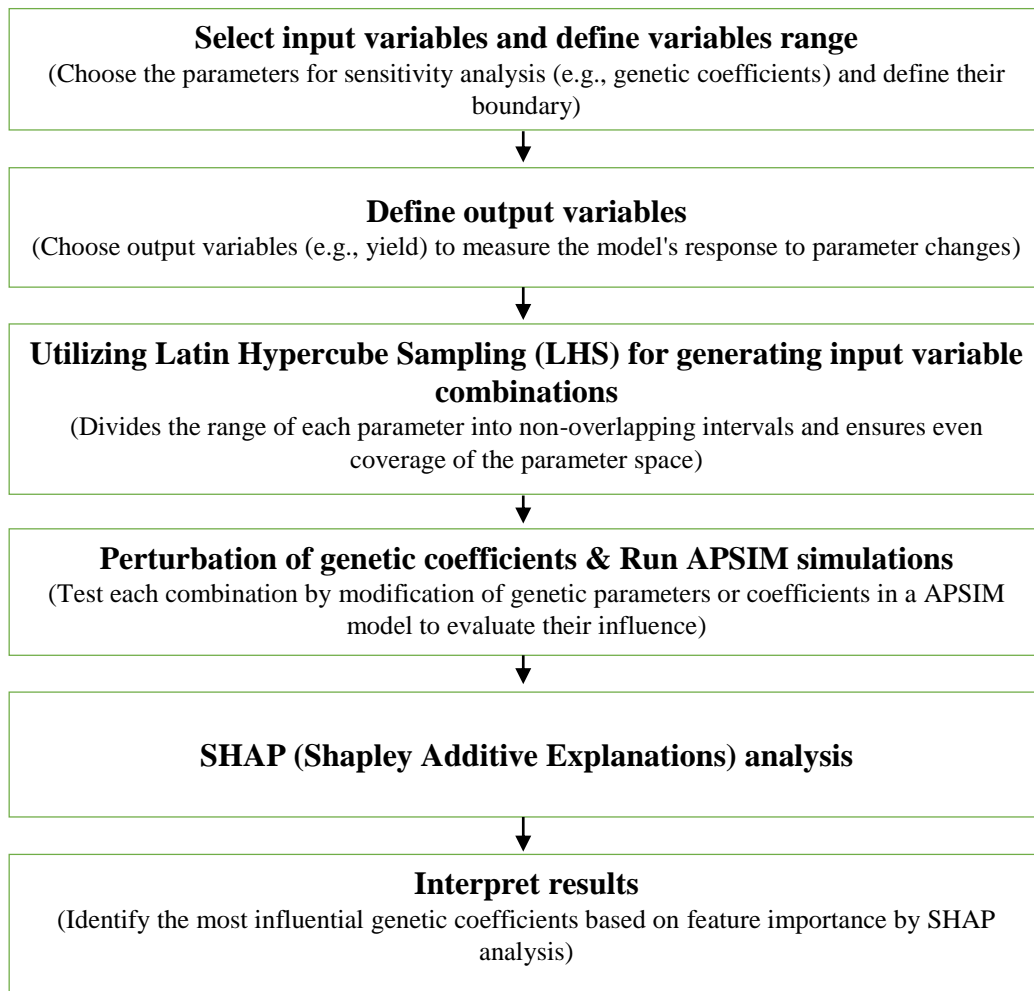
**Fig. 1: Workflow of local sensitivity analysis of genetic coefficient in the CANEGRO model**

### 3.1.2 Sensitivity analysis genetic coefficient for aerial dry biomass (t/ha)

For aerial dry biomass, MaxPARCE again ranked highest with an SI of 2.25 (Figure 4), indicating a strong influence on biomass accumulation through efficient light use prior to respiration. The second most impactful parameter was APFMX (SI = 1.71), which governs the allocation of dry matter to aerial plant parts such as leaves and stems. PII was ranked third (SI = -0.564), again showing a negative effect. Higher PII values are associated with delayed leaf emergence, which can constrain leaf area development and reduce photosynthetic activity, thereby lowering biomass accumulation. These results underscore the importance of optimizing MaxPARCE and APFMX for enhancing above-ground biomass.

### 3.1.3 Sensitivity analysis genetic coefficient for sucrose content % in stalk

In terms of sucrose accumulation, APFMX was the most sensitive parameter, with an SI of 9.45, showing a strong positive effect on sucrose content. A higher value of APFMX leads to increased aerial biomass production, indirectly boosting sucrose synthesis through enhanced photosynthetic activity. STKPFMAX (SI = 0.725) ranked second, influencing the partitioning of assimilates toward stalks, which serve as the primary storage sites for sucrose. The third key parameter was SUCA (SI = 0.647), which regulates sucrose accumulation at the base of the stalk. Although its impact was less than the top two, it still plays a notable role in sugar content simulation.



**Fig. 2: Workflow of global sensitivity analysis of genetic coefficient in the APSIM mod**

#### 3.1.4 Sensitivity Analysis of Genetic Coefficients for LAI (Leaf Area Index)

LFMAX, with an SI of 0.762, was the most critical parameter affecting LAI, as it defines the maximum number of green leaves. A higher LFMAX contributes to a larger photosynthetic surface, boosting energy capture and plant productivity. The second-ranked parameter, POPTT16 (SI = 1.18), controls stalk population, which indirectly impacts LAI through plant density and competition. P11 once again showed a negative influence (SI = -0.564), indicating that an increase in this parameter could delay leaf emergence and reduce LAI. The sensitivity results support findings by Coelho *et al.*, (2019), confirming the importance of LFMAX and P11 in optimizing canopy development.

#### 3.1.5 Sensitivity Analysis of Genetic Coefficients for Stalk Height (m)

SER0 was identified as the most influential parameter for stalk height with an SI of 1.0. It regulates the stalk elongation rate and positively contributes to final stalk length. In contrast, APFMX showed a negative sensitivity (SI = -0.99), suggesting that increased allocation to aerial biomass may limit vertical stalk growth, possibly due to trade-offs in resource distribution. P11 ranked third (SI = 0.362), positively influencing stalk height but with less impact compared to SER0.

**Table 1:** Selected parameters used to assess the parameter sensitivity of APSIM sugar model

Parameter as listed in APSIM-Sugar model (Description)	Level	Code	Lower and upper bound
Leaf_size (Leaf area of the respective leaf)	Leaf_size_no = x	LS1	500 - 2000
	Leaf_size_no = x	LS2	25000 - 70000
	Leaf_size_no = x	LS3	25000 - 70000
Cane_fraction (Fraction of accumulated biomass partitioned to cane)	-	CF	0.65 - 0.80
Sucrose_fraction_stalk (Fraction of accumulated biomass partitioned to sucrose)	Stress factor = x	SF	0.50 - 0.70
Sucrose_delay (Sucrose accumulation delay)	-	SD	0 - 600
Min_sstem_sucrose (Minimum stem biomass before partitioning to sucrose commences)	-	MSS	450 - 1500
Min_sstem_sucrose_redn (Reduction to minimum stem sucrose under stress)	-	MSSR	0 - 20
Tt_emerg_to_begcane (Accumulated thermal time from emergence to beginning of cane)	-	EB	1200 - 1900
Tt_begcane_to_flowering (Accumulated thermal time from beginning of cane to flowering)	-	BF	5500 - 6500
Tt_flowering_to_crop_end (Accumulated thermal time from flowering to end of the crop)	-	FC	1750 - 2250
Green_leaf_no (Maximum number of fully expanded green leaves)	-	GLN	9 - 14
Tillerf_leaf_size (Tillering factors according to the leaf numbers)	Tiller_leaf_size_no = x	TLS1	1 - 6
	Tiller_leaf_size_no = x	TLS2	1 - 6
	Tiller_leaf_size_no = x	TLS3	1 - 6
	Tiller_leaf_size_no = x	TLS4	1 - 6
	Tiller_leaf_size_no = x	TLS5	1 - 6
Transp_eff (Transpiration efficiency coefficient)	Stage_code = 1 (Sowing)	TE1	0.008 - 0.014
	Stage_code = 2 (Sprouting)	TE2	0.008 - 0.014
	Stage_code = 3 (Emergence)	TE3	0.008 - 0.014
	Stage_code = 4 (Beginning of cane)	TE4	0.008 - 0.014
	Stage_code = 5 (Flowering)	TE5	0.008 - 0.014
	Stage_code = 6 (End of crop)	TE6	0.008 - 0.014
Rue (Radiation use efficiency)	Stage_code = 3 (Emergence)	RUE3	1.2 - 2.5
	Stage_code = 4 (Beginning of cane)	RUE4	1.2 - 2.5
	Stage_code = 5 (Flowering)	RUE5	1.2 - 2.5

**Table 2:** Selected parameters used to assess the parameter sensitivity of DSSAT CANEGRO model

Parameter	Unit	Model Maxima and Minima	Lower and upper bound
MaxPARCE (G)	g. MJ <sup>-1</sup>	5.0 - 7.0	3.0 – 11.0
APFMX (G)	t t <sup>-1</sup>	0.88 - 0.88	0.84 – 1.0
STKPFMAX (G)	t t <sup>-1</sup> on a dry mass basis	0.60 - 0.80	0.55 – 0.95
SUCA (G)	t t <sup>-1</sup>	0.50 - 0.70	0.35 – 0.85
TBFT (N)	°C	25 - 25	22 – 28
LFMAX (N)	Leaves	10 - 13	8 – 15
MXLFAREA (G)	cm <sup>2</sup>	360 - 600	300 – 700
MXLFARNO (N)	Leaves	15 - 23	12 – 25
LER0 (N)	-	0.20 - 0.30	0.15 – 0.35
PI1 (P)	°C day	50 - 90	40 – 110
PI2 (P)	°C day	107 - 170	90 – 210
PSWITCH (P)	Leaves	12 - 18	11 – 22
TDELAY (N)	-	20 - 50	10 – 80
TAR0 (N)	-	0.01 - 0.04	0.01 – 0.06
POPTT16 (P)	Stalks m <sup>-2</sup>	10 - 13.5	7.0 – 17
TTPLNTEM (N)	°C day	150 - 150	100 – 200
TTRATNEM (N)	°C day	30 - 50	10 – 80
CHUPIBASE (N)	°C day	1000 - 1500	500 – 2000
SER0 (N)	-	0.14 - 0.30	0.10 – 0.50
TT_POPGROWTH (P)	°C day	500 - 700	300 – 900
LG_AMBASE (N)	t ha <sup>-1</sup>	220 - 220	200 – 300

### 3.2 Global sensitivity analysis of genetic coefficients in APSIM model

The SHAP summary plot (Figure 5 and 6) provides insights into the relative influence of different APSIM genetic coefficients on sugarcane growth and yield attributes. Features with high SHAP values indicate a stronger influence on model output, where positive values tend to increase the output values and negative values tend to decrease it. For cane yield, RUE of growth stage 4 (from beginning of cane growth to flowering; RUE4) exhibits the highest impact, followed by RUE of growth stage 3 (from emergence to beginning of cane growth; RUE3), TE4, and GLN (Figure 5a). Other factors, such as CF, SF, and TLS, also contribute to yield variations, though their influence is comparatively less significant. This result is in good agreement with the findings of Gunarathna *et al.*, (2019).

The SHAP summary plot for CCS reveals that MSS (minimum stem biomass before partitioning to sucrose

commences), RUE4, and SF are the most influential features, exhibiting the highest SHAP values and indicating their significant impact on model predictions (Figure 6a). Additionally, RUE3, TLS1, and GLN contribute notably, while features such as FC, MSSR, and EB play a moderate role in determining CCS. The observed feature importance aligns well with the findings of Gunarathna *et al.*, (2019), who reported that MSS has a greater effect on CCS than RUE3. This consistency reinforces the reliability of the model and underscores the critical role of MSS in sucrose accumulation.

For the LAI, GLN (maximum number of fully expanded green leaves) and CF (Cane fraction) are the most influential features, exhibiting the highest SHAP values, followed by TE4, RUE3, and RUE5 (Figure 5b).

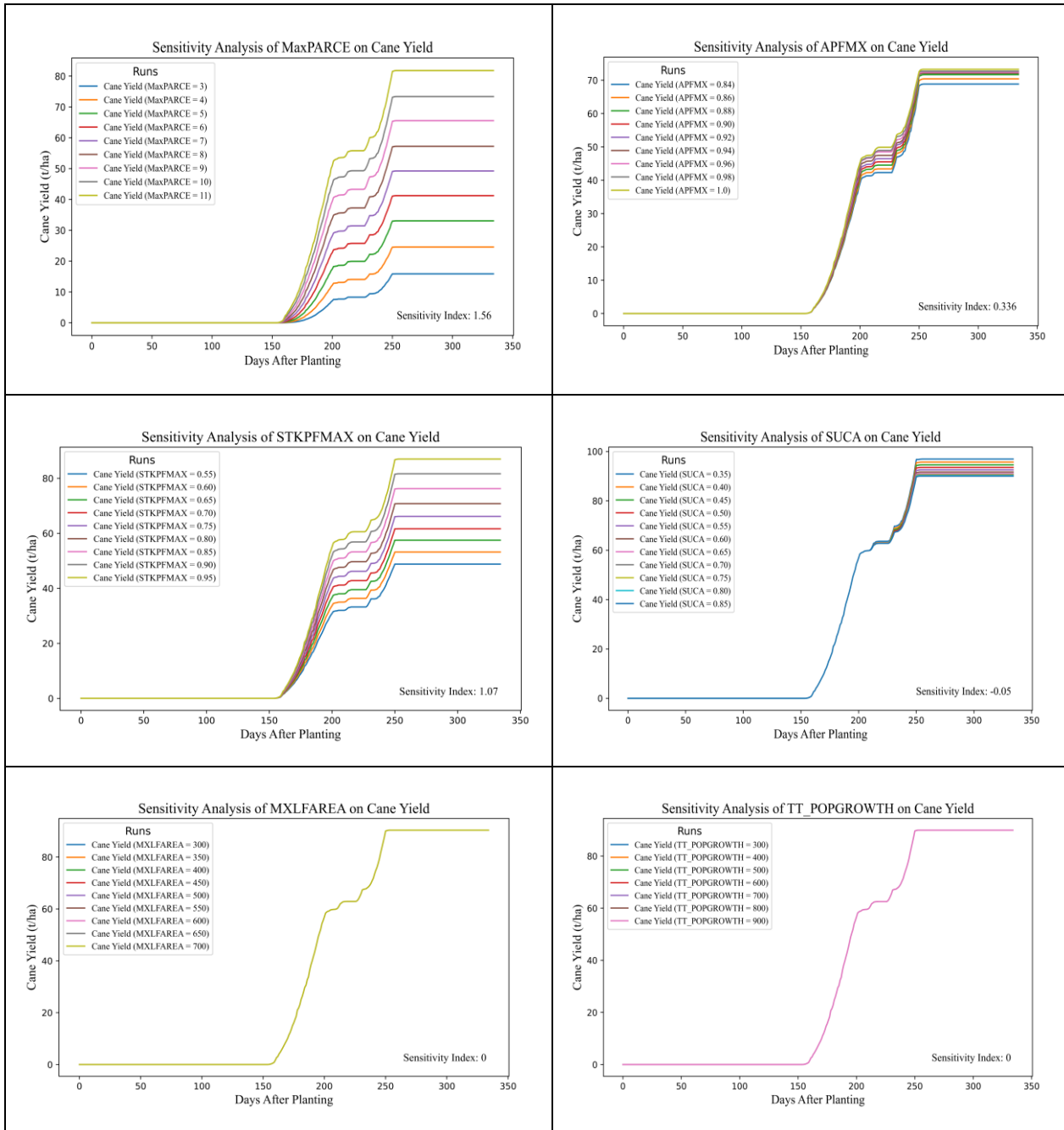


Fig. 3: Sensitivity analysis of sugarcane genetic coefficient for cane yield

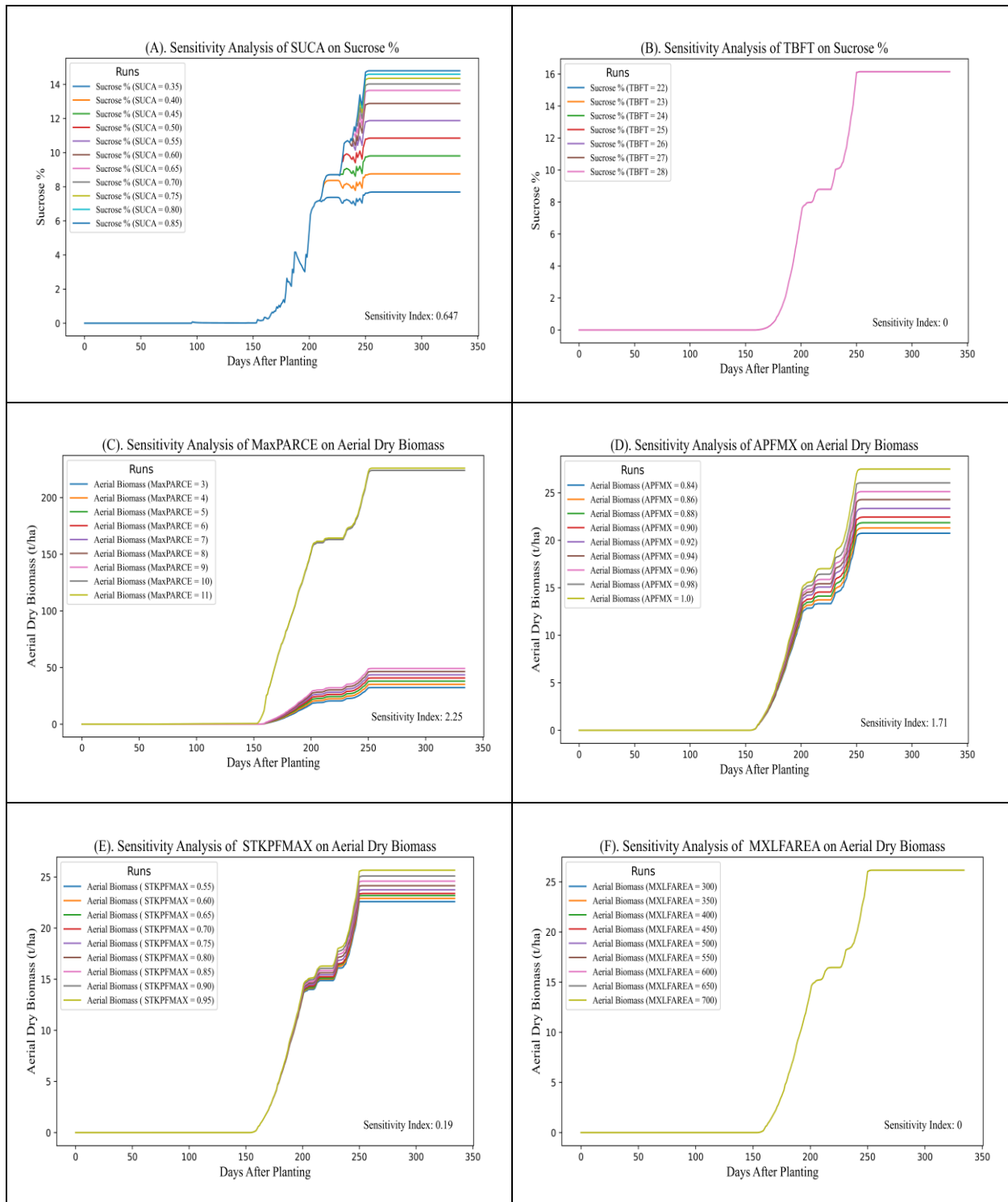
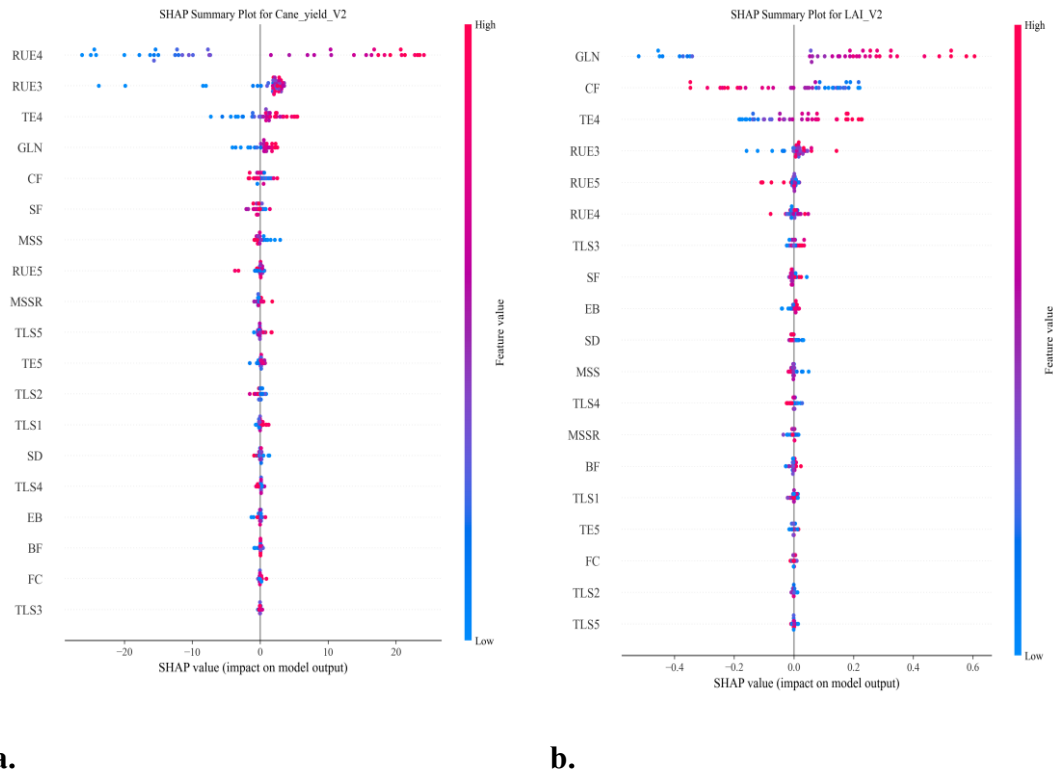
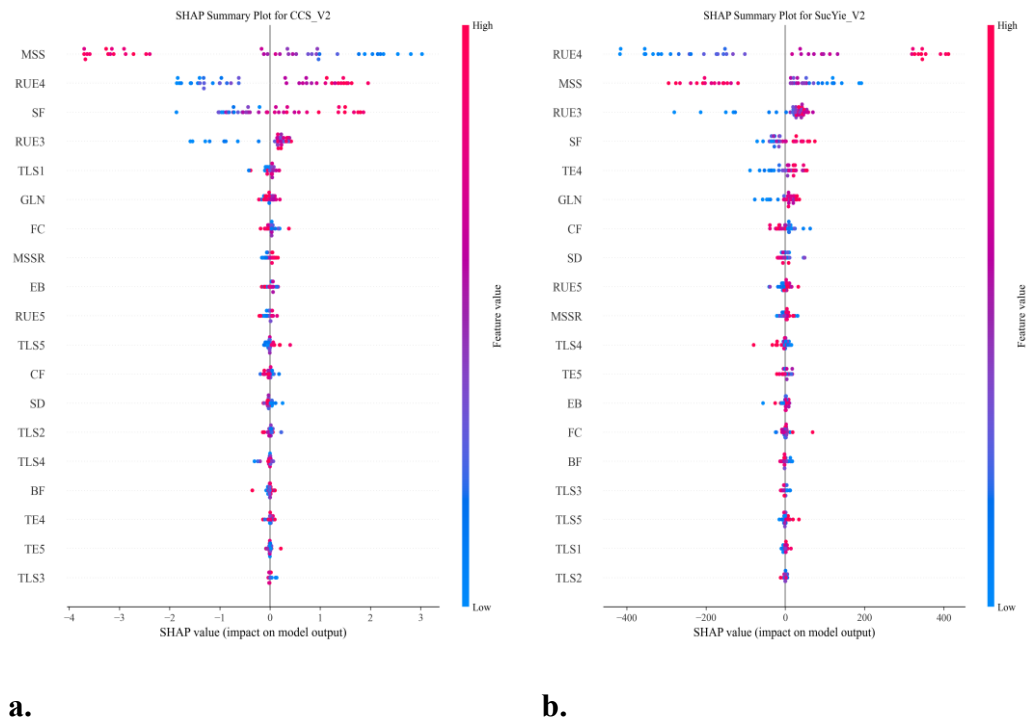


Fig. 4: Sensitivity analysis of sugarcane genetic coefficient for sucrose % and aerial dry biomass



**Fig. 5:** Sensitivity of APSIM-Sugar to parameters influencing (a) cane yield (t/ha) and (b) LAI, based on SHAP analysis



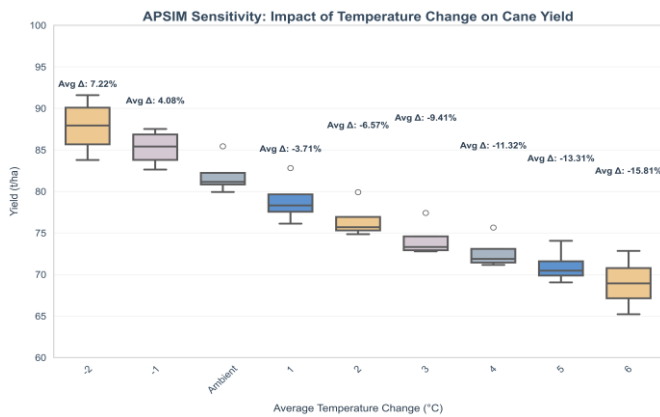
**Fig. 6:** Sensitivity of APSIM-Sugar to parameters influencing (a) CCS (%) and (b) sucrose yield (g/m<sup>2</sup>), based on SHAP analysis

The SHAP summary plot for sucrose yield ( $\text{g/m}^2$ ) indicates that RUE4, MSS, and RUE3 are the most influential features, exhibiting the highest SHAP values and demonstrating their strong impact on model output (Figure 6b). SF, TE4, and GLN also contribute notably, while CF, SD, and RUE5 play a moderate role in determining sucrose yield. Features such as MSSR, TLS4, and TE5 have comparatively lower influence. The observed feature importance aligns well with the findings of Gunarathna *et al.*, (2019), who reported that RUE4 and MSS are the primary drivers influencing sucrose yield ( $\text{g/m}^2$ ) in the APSIM sugar model.

### 3.3 Model sensitivity analysis for climatic parameters

#### 3.3.1 APSIM and CANEGRO models sensitivity to temperature variation

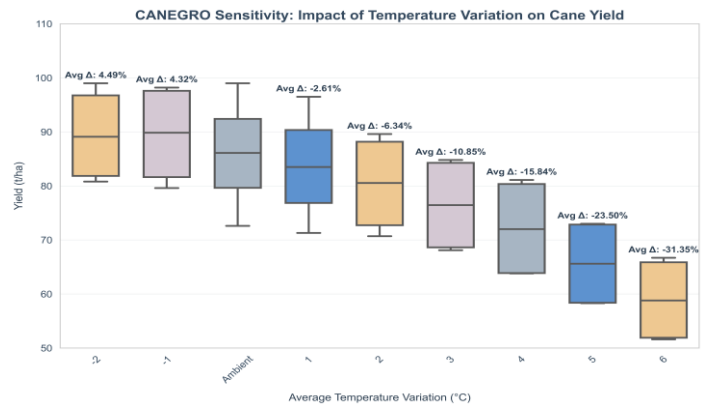
The APSIM and CANEGRO models show contrasting sensitivities of sugarcane yield to temperature changes (Figures 7 and 8). Both indicate yield increases at lower temperatures ( $-2^\circ\text{C}$  and  $-1^\circ\text{C}$ ), but yield declines with rising temperatures. APSIM shows a gradual decline, with a 15.81% reduction at  $+6^\circ\text{C}$  (Figure 7), indicating moderate sensitivity and better tolerance to mild warming. In contrast, CANEGRO reveals a steeper decline, with a 31.35% yield loss at  $+6^\circ\text{C}$  and greater variability, suggesting higher sensitivity (Figure 8). These findings align with Verma *et al.*, (2023), Sonkar *et al.*, (2020), and Pandey (2023), who also reported yield reductions with increased temperatures.



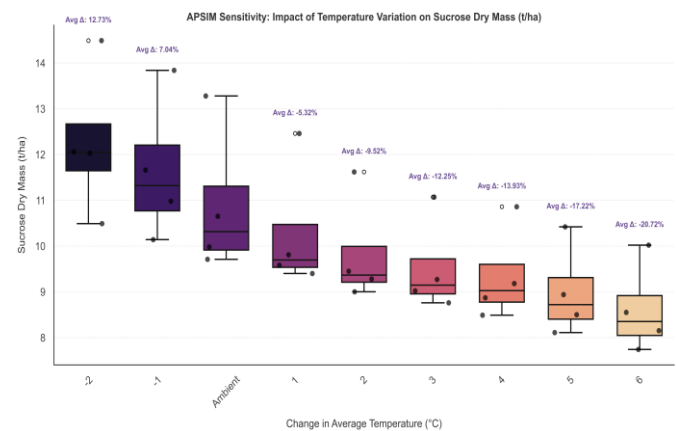
**Fig. 7:** APSIM sensitivity of sugarcane yield (t/ha) to temperature variation

The APSIM and CANEGRO models both show that sucrose dry mass declines with rising temperatures and improves under cooler conditions. APSIM predicts a sucrose yield drop of  $-5.32\%$  to  $-20.72\%$  for  $+1^\circ\text{C}$  to  $+6^\circ\text{C}$  (Figure

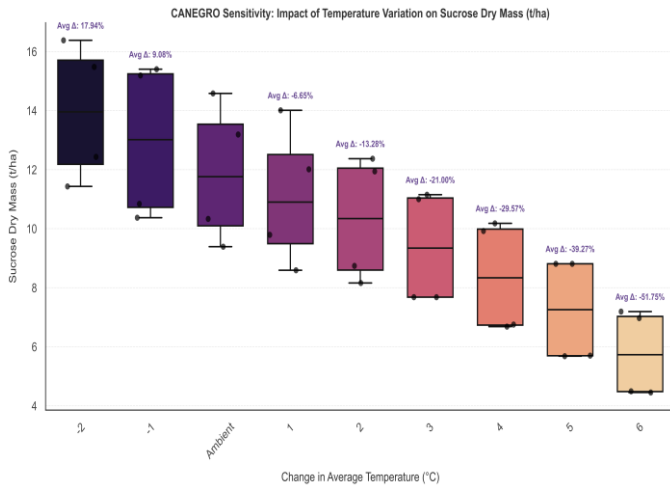
9), while CANEGRO shows a steeper decline of  $-6.65\%$  to  $-51.75\%$  (Figure 10). In contrast, decreases of  $1^\circ\text{C}$  and  $2^\circ\text{C}$  result in yield gains of 7.04% and 12.73% (APSIM) and 9.08% and 17.94% (CANEGRO). CANEGRO shows greater sensitivity to heat stress, consistent with Shanthi *et al.*, (2023), who reported significant sucrose losses under future climate scenarios. The decline in sucrose is linked to reduced activity of key enzymes like sucrose phosphate synthase (SPS) and sucrose synthase (SS) at high temperatures (Gomathi *et al.*, 2021), which disrupts sucrose synthesis and accumulation.



**Fig. 8:** CANEGRO sensitivity of sugarcane yield (t/ha) to temperature variation



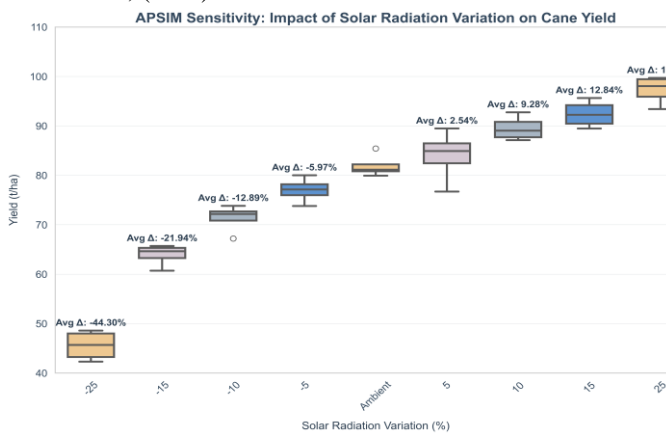
**Fig. 9:** APSIM sensitivity of sucrose dry mass (t/ha) to temperature variation



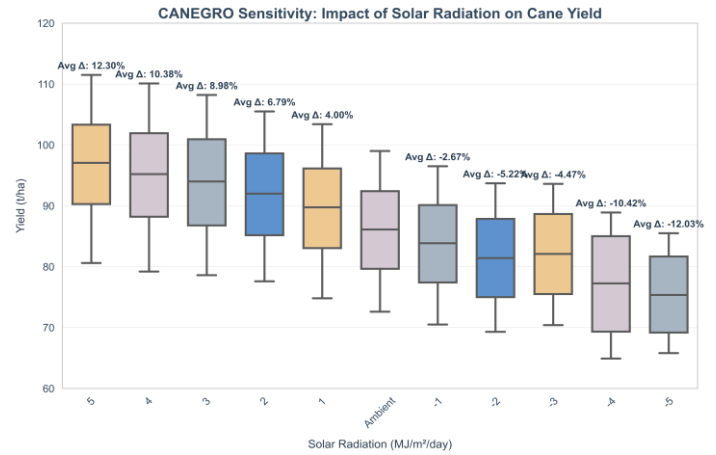
**Fig. 10:** CANEGRO sensitivity of sucrose dry mass (t/ha) to temperature variation

3.3.2 APSIM and CANEGRO models sensitivity to solar radiation variation

In the APSIM model (Figure 11), cane yield decreases sharply with reduced solar radiation—showing a 44.3% drop at a 25% reduction—while a 25% increase boosts yield by 18.85%. This indicates a nearly linear response with diminishing gains at higher radiation levels. The CANEGRO model (Figure 12) shows a similar trend but with milder sensitivity, recording a 12.03% yield loss and a 12.3% gain for a  $\pm 5$  MJ/m<sup>2</sup>/day change. Both models confirm the negative impact of reduced solar radiation and the positive effect of increased radiation, aligning with Verma *et al.*, (2023).

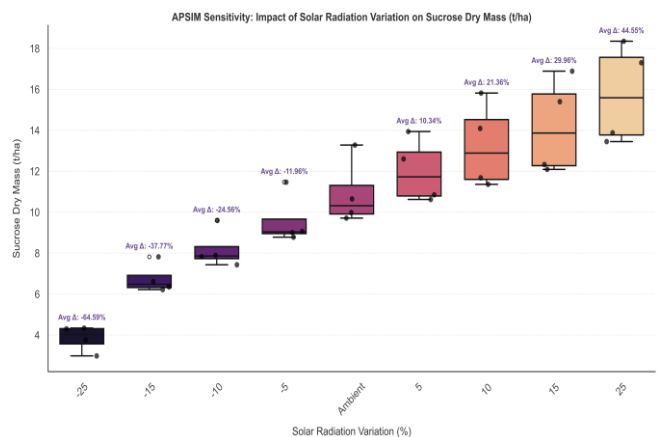


**Fig. 11.** APSIM sensitivity of cane yield (t/ha) to solar radiation variation

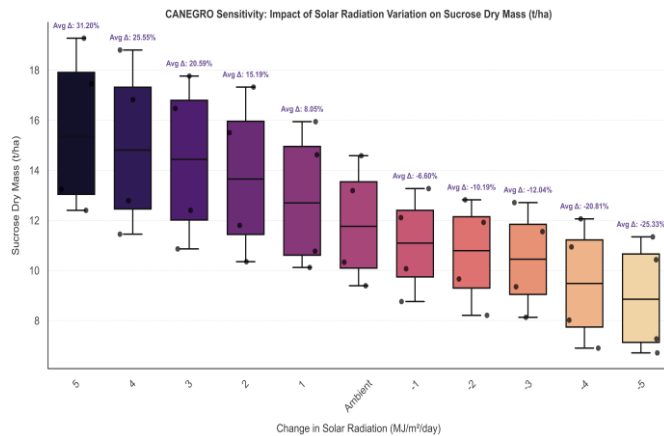


**Fig. 12:** CANEGRO sensitivity of cane yield (t/ha) to solar radiation variation

Sensitivity analysis shows that sucrose dry mass is highly responsive to solar radiation in both models. In the APSIM model (Figure 13), reductions of -25%, -15%, and -10% in solar radiation led to sharp declines of 64.59%, 37.77%, and 24.56%, respectively. In contrast, increases of +5% to +25% resulted in sucrose gains ranging from 10.34% to 44.55%, emphasizing the strong positive influence of radiation. Similarly, the CANEGRO model (Figure 14) showed declines of 25.33% and 20.81% with -5 and -4 MJ/m<sup>2</sup>/day reductions, while +4 and +5 MJ/m<sup>2</sup>/day increases boosted sucrose by 25.55% and 31.20%. Near-ambient changes ( $\pm 1$  MJ/m<sup>2</sup>/day) had modest effects, ranging from -10.19% to +8.05%. Both models confirm that solar radiation strongly influences sucrose accumulation, with APSIM showing greater sensitivity.



**Fig. 13:** APSIM sensitivity of sucrose dry mass (t/ha) to solar radiation variation



**Fig. 14:** CANEGRO sensitivity of sucrose dry mass (t/ha) to solar radiation variation

## 5. Conclusion

Sensitivity analyses emphasized the importance of specific genetic coefficients in both models. In CANEGRO, parameters related to photosynthetic efficiency and biomass partitioning (MaxPARCE, APFMX, STKPFMAX) were most influential, while in APSIM, radiation use efficiency (RUE4, RUE3), sucrose partitioning (MSS, SF), and nitrogen response (GLN) played critical roles in determining crop productivity. These findings underscore the need for targeted calibration of key parameters to improve model accuracy and realism.

Additionally, both models demonstrated significant sensitivity to climatic factors. Rising temperatures negatively impacted yield, with CANEGRO showing greater vulnerability than APSIM. Conversely, increased solar radiation was beneficial to crop productivity in both models. These insights are particularly relevant for future climate adaptation strategies in sugarcane cultivation.

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## Declarations

### Author contributions

**V. B. Virani:** Conceptualization, Methodology, Data Collection, Processing, and Analysis. **Dr. Bheem Pareek:** Writing - Original Draft, Visualization. **Dr. Siva K. Balasundram:** Writing - Original Draft.

### Funding Statement

This research was conducted without external financial support, reflecting the independent efforts and commitment of the authors.

### Data Availability

The datasets generated and/or analysed during the current study are available in a publicly accessible repository.

### Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

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