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RESEARCH ARTICLE

Comparative Evaluation of APSIM and CANEGRO Models for Simulating Sugarcane Growth and Yield

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Abstract

This study investigates the performance of the APSIM and CANEGRO crop models in simulating sugarcane growth and yield under different growing environment and fertilizer application. Field experimental data from the 2023–24 season were employed for model calibration, while validation was conducted using data from the 2024–25 season. During calibration, the CANEGRO model demonstrated limited responsiveness to variations in fertilizer dosage, producing uniform outputs across different nutrient treatments. Model validation results indicate that APSIM outperformed CANEGRO in simulating key agronomic parameters including cane yield, aerial dry biomass, and days to emergence. APSIM achieved a higher coefficient of determination ($R^2 = 0.93$), D-index (0.95), and lower RMSE (6.01 t/ha) for cane yield compared to CANEGRO ($R^2 = 0.88$, D-index = 0.77, RMSE = 6.29 t/ha).

Keywords: Calibration; Validation; CANEGRO; APSIM; Crop Modelling

1. Introduction

Sugarcane is a valuable crop and has a major economic value in that it can be utilized in both food and industrial sectors. India is the second-largest sugar producer after Brazil, which is dependent on this crop in its agro-processing industry. As the greenhouse gases are increasing with the increase in transportation needs, biofuels are also being considered as a cleaner substitute. India responded by implementing a 2018 National Biofuel Policy that has enabled the use of sugarcane juice, which is used to produce ethanol, as a sign of the increasing role of sugarcane in sustained energy solutions.

The concept of crop simulation models has come up as invaluable analytical tools in contemporary agrometeorology and management of the agricultural systems. These models, including the Agricultural Production Systems sIMulator (APSIM), the Decision Support System for Agrotechnology Transfer (DSSAT) and InfoCrop, allow researchers to simulate crop phenology, biomass buildup and ultimate yield precisely in extraordinarily varied environmental circumstances by mathematically modeling the intricate and non-linear interactions in the soil-plant-atmosphere continuum. One of the most common uses of these models is the optimization of agronomic control; they enable the researcher to experimentally simulate the effect of planting date and fertilizer management and irrigation timing changes, thus maximizing the efficiency of resource utilization at a level that cannot be done because of the prohibitive costs of agronomic field experiments on the scale and duration of the experiment (Holzworth *et al.,* 2014; Jones *et al.,* 2003). Moreover, when combined with the growing climatic variability, crop models have become quite widely used in evaluating the susceptibility of agricultural systems to changing climatic conditions in terms of temperature and precipitation. These tools can be used to simulate future climate conditions by combining downscaled outputs of General Circulation Model (GCM) to develop specific, resilient adaptation options (Rosenzweig *et al.,* 2014). In addition to field-level management, these predictive models are essential in regional yield forecasting, yield gap analysis and strategic policy decisions in sustainable agro-ecosystem management and food security around the world (Aggarwal *et al.,* 2006; Boote *et al.,* 2013).

The CANEGRO model is a source sink model of sugarcane whereby the volume of stalk is an indicator of sink strength. The energy balance leads to canopy development, and the radiation intercepted causes photosynthesis. The biomass is distributed to various parts of the plant depending on the growth, temperature and water stress and stalk partitioning is a nonlinear relationship that is affected by environmental factors (Singh *et al.,* 2010). It has been applied in the phenological study, variability of yield (Inman-Bamber,1991), regional productivity (Inman-Bamber *et al.,*1998), and bioenergy potential (Jones *et al.,*2006). Equally, APSIM-Sugar is a sugarcane specific process-based model which combines climate, soil, and crop physiology to determine yield, water utilization, and nutrient interactions (Keating *et al.,* 1999). It helps realise the agronomic processes to the optimum and evaluate the sustainability in different conditions (Singels *et al.,* 2008; Robertson *et al.,* 2017).

In this study, the APSIM and CANEGRO models were calibrated and validated for sugarcane, ensuring their reliability for future applications.

2. Materials and Methodology

2.1 Experimental Site

A two-year field study (2023 -24 and 2024 -25) at the Agronomy farm of the Navsari Agricultural University (NAU), Navsari (20°57′ N, 72°54′ E, 12 m a.s.l.) was used to calibrate and validate the crop simulation models. The two varieties of sugarcane sets (CoN 15071 and CoN 13072) planted on two planting dates (25 January and 25 February) and exposed to three fertilizer management regimes (100, 75, and 50 of the recommended doses of fertilizer) were tested.

2.2 Simulation modeling of sugarcane

2.2.1 Preparation of Input Files

The following input files have been prepared in required format of DSSAT CANEGRO (v 4.8) model and APSIM sugar Classic (v 7.10) model.

Weather file: A weather file, which was based on four significant weather meteorological parameters viz; maximum temperature, minimum temperature, length of sunshine (hours)/solar radiation (MJ/m2 /day), and rainfall (mm) on daily basis, was transformed into model required specific format.

Crop management file: Crop management file was generated using the agronomic practices, such as planting dates, cultivars, the amount of planting material and the harvesting dates. Moreover, the time of the irrigation and the quantity of irrigation, the application of fertilizers as recommended, were included in the model inputs in both planting seasons. The DSSAT experiment/crop management file was built using these inputs and the simulation tree of the APSIM Sugar model was built using these inputs.

Soil management file: The depth-wise data on percentages of sand, silt, and clay, bulk density, pH, initial soil water content, field capacity, permanent wilting point, and saturation water content was developed and formatted as per the need of the concerned models.

Genetic coefficients: DSSAT-CANEGRO and APSIM Sugar models were calibrated with two sugarcane cultivars, that is CoN 15071 and CoN 13072. Calibration was done by first alignment of the phenological coefficients to the development stages of the crop and then the growth and yield coefficients adjusted to give the simulated growth and yield close to the actual values.

2.2.2 Calibration of the Model

Models were calibrated with data obtained in the field experiments that were performed in the first season of the sugarcane (2023-24) at the Agronomy Farm of NAU, Navsari.

2.2.3 Validation of the Model

The models were validated using the data of field experiments that would be carried out in the second sugarcane season (2024-25) within the Agronomy Farm of NAU, Navsari.

3. Results and Discussion

3.1 Calibrated Genetic Coefficient of Cultivars

The calibration of crop cultivars genetic coefficients is a critical step in ensuring the accurate simulation of crop phenology, growth, and yield of specific cultivars within crop models. In this study, the genetic coefficient of sugarcane cultivars CoN 15071 and CoN 13072 were calibrated manually within the CANEGRO and APSIM models. The calibration process involved iterative adjustments of key genetic parameters. The observed field data of 2022-23 sugarcane season, including day to emergence, cane yield (t/ha), and aerial dry biomass (t/ha) served as benchmarks for comparison with model outputs during the calibration stage. Initial simulations were

Table 1: Calibrated genetic coefficients for sugarcane cultivars in the CANEGRO model

Parameter	Category	Default	Calibrated Genetic Coefficient	
		CP 88-1762	CON15071	CoN13072
MaxPARCE (G)	Biomass accumulation	5.70	10.90	11.60
APFMX (G)	Biomass partitioning	0.880	0.990	0.980
STKPFMAX (G)		0.700	0.980	0.990
SUCA (G)	Sucrose accumulation	0.580	0.820	0.840
TBFT (N)		25.0	26.0	26.0
LFMAX (N)	Canopy - leaves	12.0	13.0	13.0
MXLFAREA (G)		360.0	600.0	620.0
MXLFARNO (N)		15.0	15.0	15.0
LER0 (N)		0.250	0.250	0.250
PI1 (P)	Leaf phenology	69.0	97.0	99.0
PI2 (P)		169.0	199.0	195.0
PSWITCH (P)		18.0	18.0	18.0
TDELAY (N)	Tiller phenology	50.0	50.0	50.0
TAR0 (N)		0.020	0.020	0.020
POPTT16 (P)		13.30	11.30	13.30
TTPLNTEM (N)	Phenology	80.0	250.0	270.0
TTRATNEM (N)		30.0	50.0	50.0
CHUPIBASE (N)		1050.0	1050.0	1050.0
SER0 (N)		0.140	0.140	0.140
TT_POPGROWTH (N)		600.0	500.0	550.0
LG_AMBASE (N)	Lodging	220.0	220.0	220.0

conducted using default parameters or coefficients from closely related cultivars, followed by systematic adjustment to minimize discrepancies between simulated and observed values. The calibration was validated using an independent dataset, ensuring the robustness and reliability of the calibrated parameters. Table 1 and Table 2 present the calibrated genetic coefficients of sugarcane cultivars for the APSIM and CANEGRO models, respectively.

3.2 Validation of CANEGRO and APSIM model

Model validation involves assessing a model's accuracy by comparing its simulated results with independent observed data to verify its reliability under varying conditions. In this study, validation was performed using independent datasets from the second sugarcane season of the 2023–24 field experiment, which included parameters such as days to emergence, cane yield (t/ha), and aerial dry biomass (t/ha). The experiment included 12 treatment combinations involving variations in fertilizer application, sowing dates, and cultivars. The CANEGRO model, however, showed limited sensitivity to fertilizer treatments, with simulations largely influenced by sowing dates and cultivar-specific environmental conditions. This limitation is supported by findings from Singels *et al.,* (2008) and Coelho *et al.,* (2019), who reported the model's lack of response to fertilization, leading to its exclusion from model inputs. Similarly, Sharma (2019) found CANEGRO ineffective in simulating nitrogen-related responses.

In contrast, the APSIM model responded well to the treatment variations, effectively simulating observed differences in growth, yield, and related parameters. This highlights APSIM's superior adaptability and accuracy in capturing the influence of diverse agronomic practices.

3.2.1 Cane yield (t/ha)

The performance of APSIM and CANEGRO models in simulating sugarcane yield (t/ha) is summarized in Figure 1. APSIM showed excellent accuracy during calibration, with MAE of 2.81 t/ha, RMSE of 3.71 t/ha, MAPE of 3.72%, R^2 of 0.95, and D-Index of 0.98. In validation, performance slightly declined with MAE of 5.39 t/ha, RMSE of 6.01 t/ha, MAPE of 7.51%, R^2 of 0.93, and D-Index of 0.95. These results align with Peng *et al.,* (2020) and

Dias *et al.,* (2021), who also reported high model accuracy. In comparison, CANEGRO showed lower performance. During calibration, it recorded MAE of 4.36 t/ha, RMSE of 4.75 t/ha, MAPE of 4.70%, R^2 of 0.84, and D-Index of 0.90. Validation results showed MAE of 5.04 t/ha, RMSE of 6.29 t/ha, MAPE of 5.70%, R^2 of 0.88, and D-

Index of 0.77. These findings are consistent with Parmar *et al.,* (2019) and Bhengra *et al.,* (2016). Overall, APSIM outperforms CANEGRO with lower errors and higher correlation, making it more reliable for sugarcane yield prediction.

Table 2: Calibrated genetic coefficients for sugarcane cultivars in the APSIM model

Parameter	Default (q123)		Final Calibrated Level		Final Calibrated Value	
	Level	Parameter	CoN15071	CoN13072	CoN15071	CoN13072
Leaf_size (mm^2)	Leaf_size_no = 1	1500	Leaf_size_no = 1	Leaf_size_no = 1	4000	3000
	Leaf_size_no = 14	55000	Leaf_size_no = 10	Leaf_size_no = 15	30000	30000
	Leaf_size_no = 20	55000	Leaf_size_no = 16	Leaf_size_no = 20	60000	70000
Cane_fraction (gg^{-1})	-	0.70	-	-	0.61	0.74
Sucrose_fraction_stalk (gg^{-1})	Stress factor = 1	0.55	Stress factor = 1	Stress factor = 1	0.56	0.65
stress_factor_stalk	-	0.2	-	-	0.0	0.0
Sucrose_delay (gm^{-2})	-	0.0	-	-	0.0	0.0
Min_sstem_sucrose (gm^{-2})	-	800	-	-	1300	2700
Min_sstem_sucrose_redn (gm^{-2})	-	10	-	-	08	17
Tt_emerg_to_begcane (°C day)	-	1900	-	-	1300	1240
Tt_begcane_to_flowering (°C day)	-	6000	-	-	3700	3450
Tt_flowering_to_crop_end (°C day)	-	2000	-	-	1900	2100
Green_leaf_no (No.)	-	13	-	-	11	13
Tillerf_leaf_size (mm^2 mm^{-2})	Tiller_leaf_size_no = 1	1	Tiller_leaf_size_no = 1	Tiller_leaf_size_no = 1	1	1.5
	Tiller_leaf_size_no = 4	1	Tiller_leaf_size_no = 4	Tiller_leaf_size_no = 4	1	1
	Tiller_leaf_size_no = 10	1.5	Tiller_leaf_size_no = 15	Tiller_leaf_size_no = 10	1.5	1
	Tiller_leaf_size_no = 16	1	Tiller_leaf_size_no = 19	Tiller_leaf_size_no = 16	1	2
	Tiller_leaf_size_no = 26	1	Tiller_leaf_size_no = 21	Tiller_leaf_size_no = 22	2	2.5

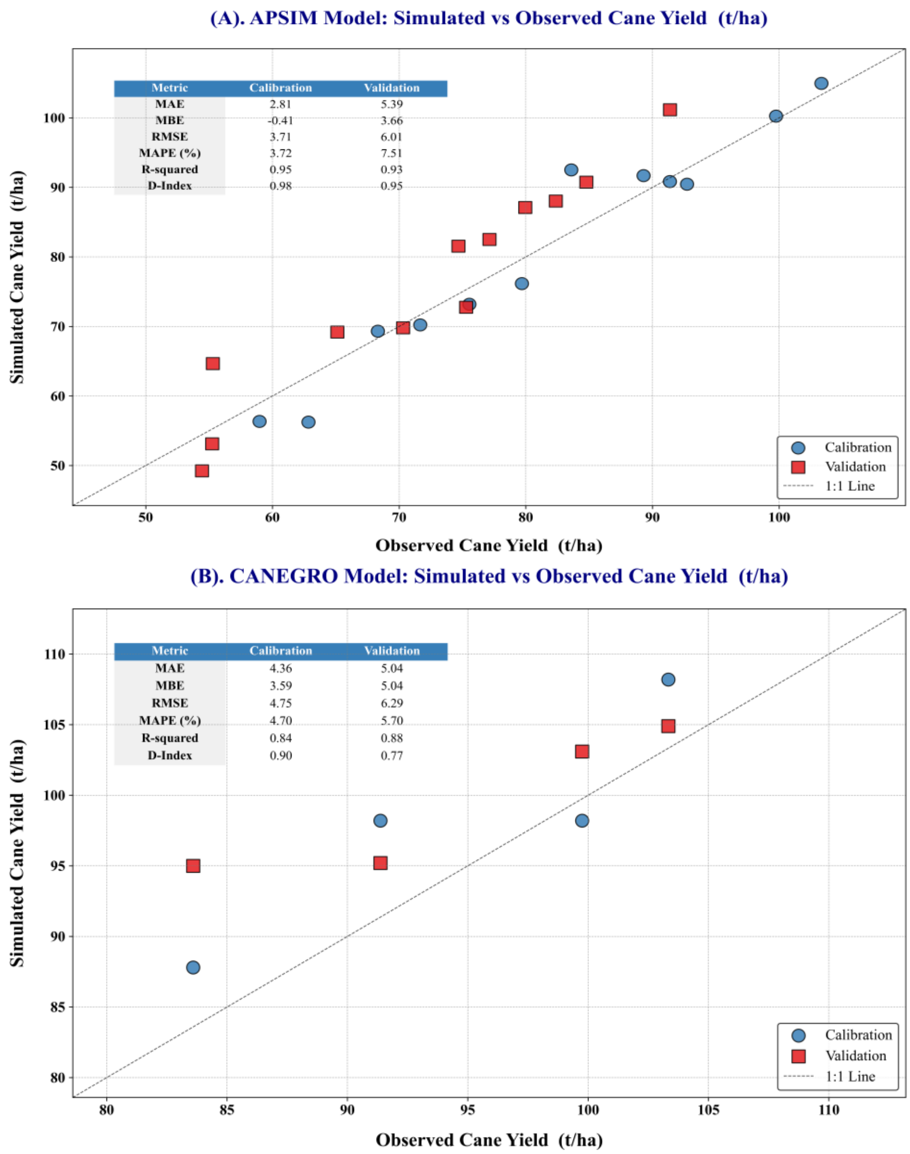

Fig. 1: Calibration and validation results of the APSIM and CANEGRO models for cane yield (t/ha)

3.2.2 Aerial dry biomass (t/ha)

The performance of APSIM and CANEGRO models in simulating aerial dry biomass (t/ha) is shown in Figure 2. APSIM achieved R^2 values of 0.82 (calibration) and 0.77 (validation), with RMSE of 3.98 t/ha and 4.72 t/ha, and D-index values of 0.86 and 0.75, indicating good calibration accuracy but moderate reliability in validation. CANEGRO showed R^2 of 0.77 (calibration) and 0.80 (validation), with RMSE of 4.51 t/ha and a much lower 1.26 t/ha during validation. D-index values were 0.51 and 0.87, showing notable improvement in validation. MAPE for CANEGRO was 12.90% (calibration) and 4.00% (validation), outperforming APSIM in validation accuracy. Singh *et al.,* (2018) reported similar results for CANEGRO with an RMSE of 4.08 t/ha and D-index of 0.89. Overall, APSIM performed better during calibration, while CANEGRO showed superior accuracy and reliability in validation, making it more suitable for simulating aerial dry biomass under similar conditions.

3.2.3 Days to emergence

The performance of APSIM and CANEGRO models in simulating days to emergence. APSIM demonstrated strong predictive ability, with R^2 values of 0.96 (calibration) and 0.73 (validation), and low errors—MAE of 2.50 and 2.00, RMSE of 2.65 and 2.55, and MAPE of 8.19% and 6.29%. However, a drop in D-index from 0.79 to 0.51 and MBE values of -2.50 and -2.00 suggest a slight underestimation and reduced model efficiency in validation.

These results are still favorable compared to Peng *et al.,* (2020), who reported an RMSE of 15.54 and R^2 of 0.76 for APSIM. The CANEGRO model showed higher accuracy during calibration, with R^2 of 0.97, MAE of 2.00, RMSE of 2.55, and MAPE of 6.87%, outperforming APSIM at this stage. However, its performance declined notably during validation—R^2 dropped to 0.39, MAE and RMSE increased to 2.55 and 2.60, and D-index reduced from 0.87 to 0.65, indicating reduced reliability. The MBE improved slightly (-2.00 to -0.25), suggesting less bias in validation. Results align with Parmar *et al.,* (2019) and Singh *et al.,* (2018), who reported RMSE around 2.2 and D-index values between 0.70 and 0.90. Overall, APSIM showed more consistent performance across both phases, while CANEGRO had better calibration accuracy but weaker validation reliability.

3.2.4 LAI

Figure 3 illustrates the comparative performance of the APSIM and CANEGRO models in simulating Leaf Area Index (LAI). Overall, APSIM demonstrated superior accuracy and reliability, showing strong correlation with observed data ($R^2 = 0.85$) for calibration; 0.68 for validation) alongside low error metrics (RMSE = 0.74 and 0.65, respectively) and high D-Index scores (0.72 and 0.74). In contrast, CANEGRO exhibited poor predictive capability ($R^2 = 0.36$ for both phases)

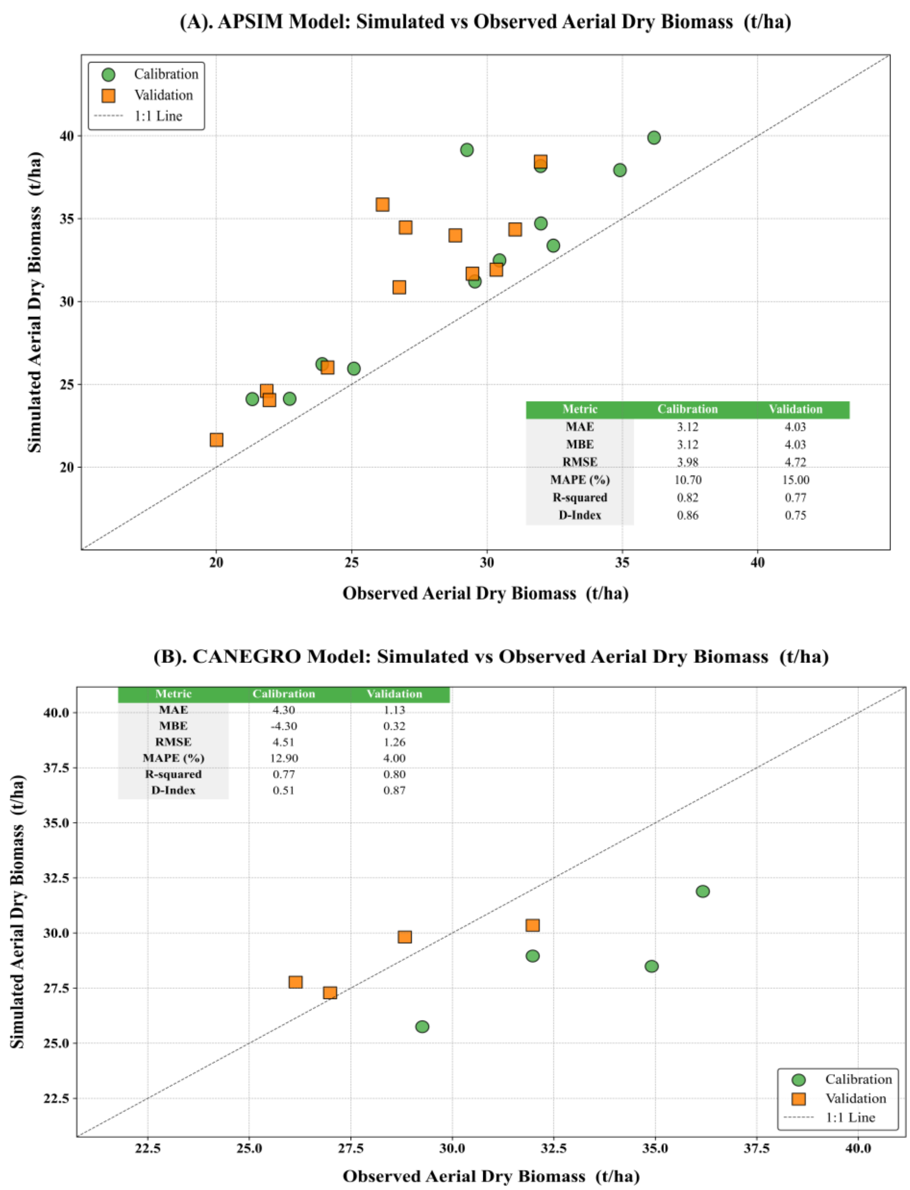

Fig. 2: Calibration and validation results of the APSIM and CANEGRO models for aerial dry biomass (t/ha)

yielding higher error margins (validation RMSE = 1.11, MAPE = 22.80%) and struggling to replicate LAI variability (validation D-Index = 0.18). Furthermore, CANEGRO's Mean Bias Error revealed inconsistent under- and over-estimations. While previous studies (e.g., Singh *et al.,* 2018) report even higher simulation precision, these results clearly establish APSIM as the more suitable framework for LAI estimation in this study, though further parameter refinement is recommended for both models.

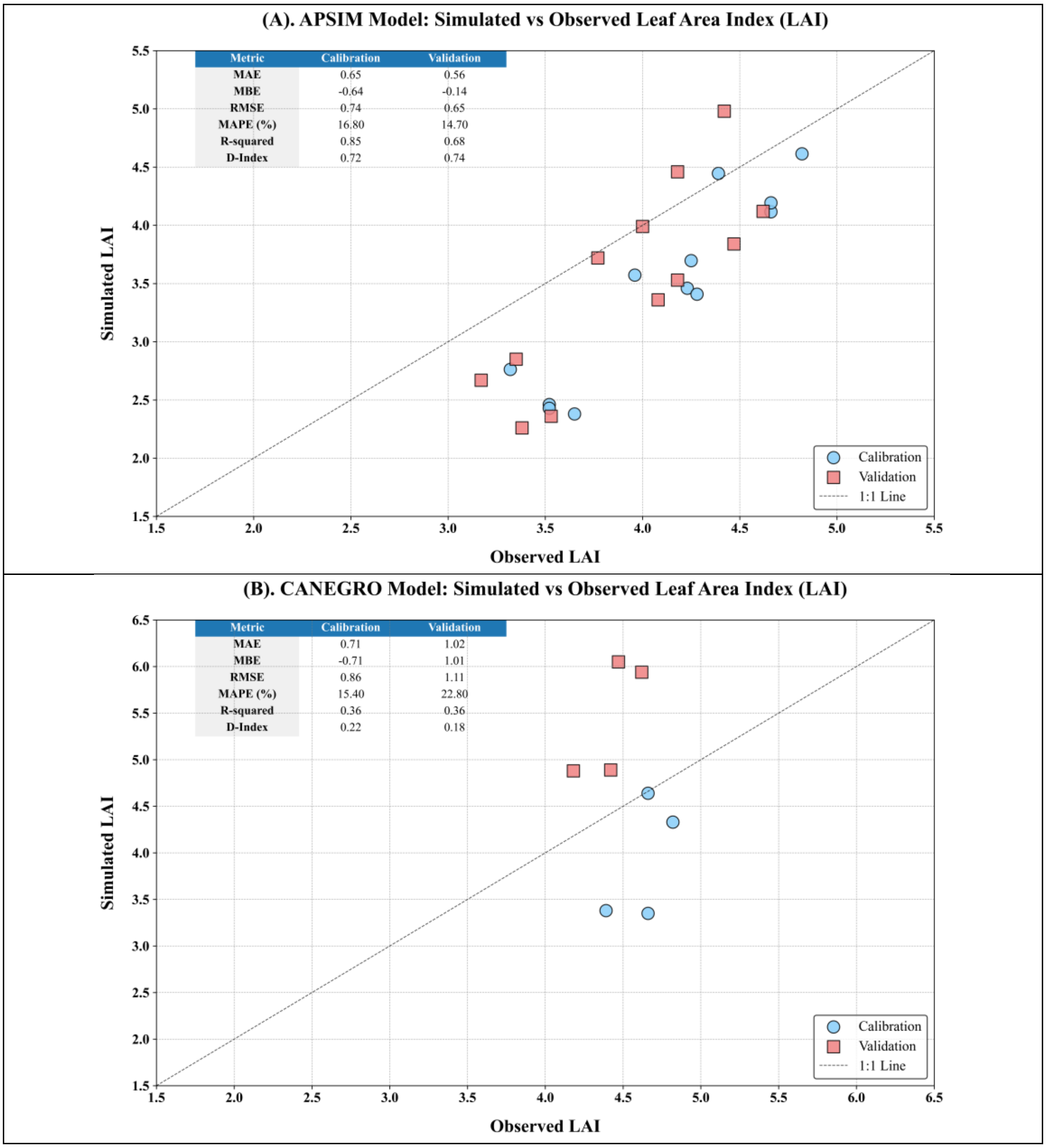

Fig. 3: Calibration and validation results of the APSIM and CANEGRO models for LAI

3.2.5 Stalk dry mass (t/ha)

The performance of the APSIM and CANEGRO models in simulating stalk dry mass (t/ha). Overall, APSIM exhibited strong and consistent predictive accuracy across both phases, yielding low error metrics (calibration and validation RMSE of 2.31 t/ha and 2.28 t/ha, respectively) and a highly stable Mean Absolute Percentage Error (MAPE) of 8%. The model demonstrated exceptional efficiency and minimal systematic bias, maintaining high D-Index scores of 0.90 for calibration and 0.89 for validation. Conversely, while CANEGRO achieved comparable R^2 values (0.82 in calibration; 0.84 in validation) and captured general trends initially, it struggled significantly with generalizability. CANEGRO overestimated stalk dry

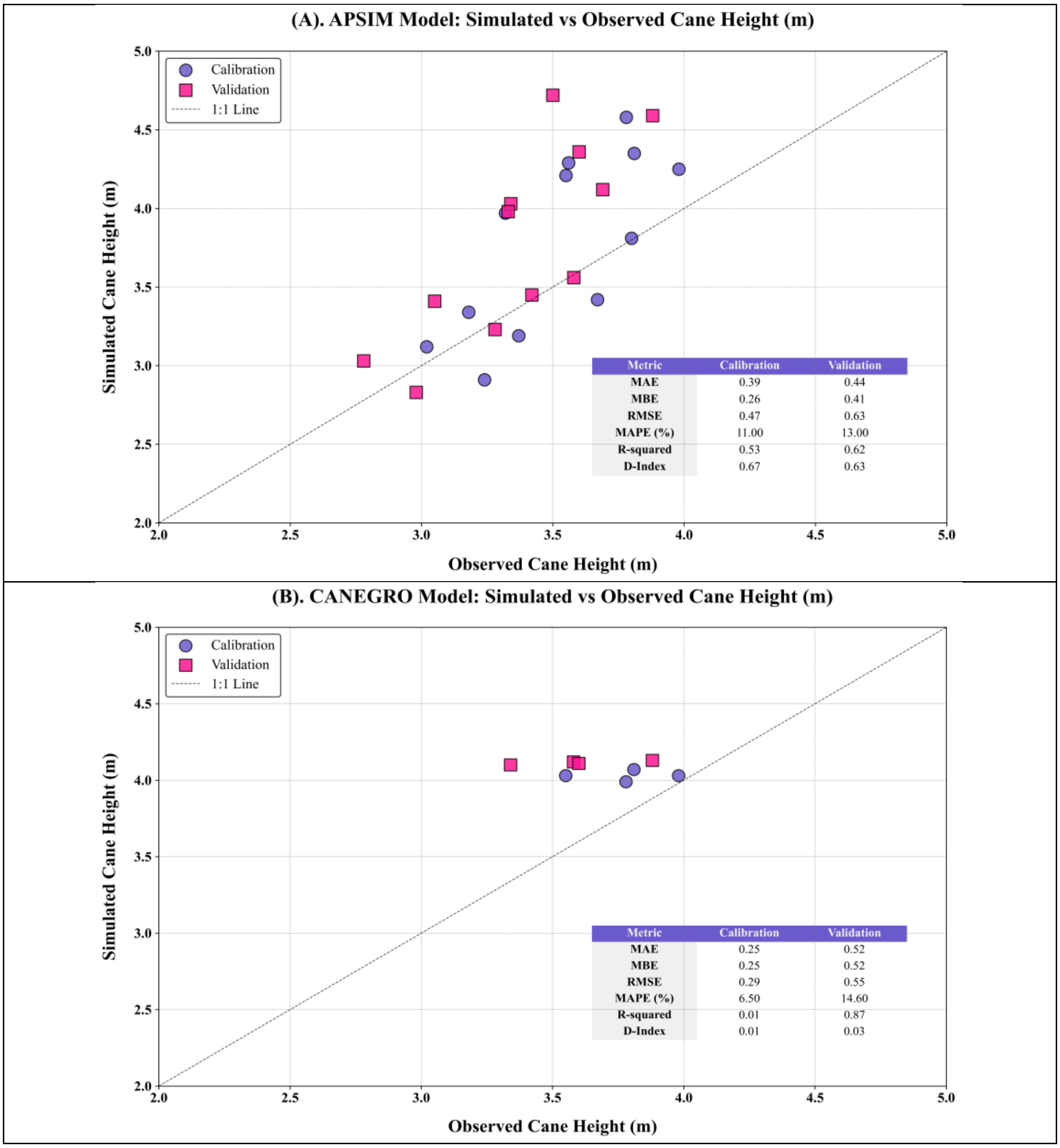

Fig. 4: Calibration and validation results of the APSIM and CANEGRO models for cane height (m)

mass during calibration (MBE = 2.71 t/ha), and its performance sharply deteriorated during validation: MAE and RMSE both escalated to 6.45 t/ha, MAPE surged to 29.30%, and the D-Index plummeted from 0.65 to a highly unreliable 0.18. Ultimately, APSIM significantly outperformed CANEGRO in all key metrics, demonstrating superior robustness and reliability for simulating stalk dry mass under varying conditions.

3.2.6 Plant height (t/ha)

Figure 4 presents the comparative simulation of plant height (m). APSIM demonstrated consistent, moderate reliability across both phases, maintaining stable D-index scores (0.67 and 0.63) and acceptable error margins (RMSE = 0.47–0.63 m), which aligns with findings by Gunarathna et al. (2018). Conversely, CANEGRO exhibited severe instability; despite a spike in validation R^2 (0.87), its D-index remained exceptionally low across both calibration (0.01) and validation (0.03), and its error margins doubled (validation MAPE = 14.6%). This poor agreement and tendency for overestimation echo previous reports (Singh *et al.,* 2010; Parmar *et al.,* 2019). Ultimately, APSIM proved significantly more robust and reliable for simulating cane height.

5. Conclusion

The comparative evaluation of the APSIM and CANEGRO crop models for simulating sugarcane growth under the agro-climatic conditions of Navsari revealed that APSIM consistently outperforms CANEGRO in terms of accuracy and responsiveness to both management and environmental variables. While the CANEGRO model demonstrated limited sensitivity to fertilizer inputs, APSIM effectively captured yield variations across nutrient treatments. Model performance metrics further confirmed the superior predictive ability of APSIM, particularly for cane yield, biomass, and crop structural parameters.

Overall, the study highlights the robustness and adaptability of the APSIM model for simulating sugarcane growth in Indian conditions and supports its use for guiding cultivar selection, management optimization, and climate change impact assessments. The findings also reinforce the importance of parameter sensitivity analysis in enhancing model calibration and application in precision agriculture.

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Declarations

Author contributions

Harsh R. Prajapati: Conceptualization, Methodology, Data Collection, Processing, and Analysis. **B. M. Mote**: Writing - Original Draft, Visualization. **Nayan Baria**: Writing - Original Draft.

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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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