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Sensitivity Analysis of Plant- and Cultivar-Specific Parameters of APSIM-Sugar Model: Variation between Climates and Management Conditions

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Received: 18 April 2019; Accepted: 11 May 2019; Published: 14 May 2019

Abstract: With increasing demand for food and energy, there is a great need for improving sugarcane productivity. New cultivars and management strategies can be assessed using process-based crop models. Information on cultivars needs to be updated frequently, but it is still limited in most crop models. Therefore, it is important to identify possible candidates for varietal parameterization and calibration. Because sensitivity analysis is computationally expensive, we used a less expensive emulator-based approach to conduct a global sensitivity analysis using the apsimr package and GEM-SA software. We studied the sensitivity of four yield outputs of the APSIM-Sugar model to 13 parameters in rainfed and irrigated conditions in Japan and Sri Lanka. Unlike previous studies, our aim was to give comprehensive insights into the variation in sensitivity due to variation in climate. The results confirmed distinct variation of parameter influence between climates and between management conditions. We identify possible candidates for parameterization and calibration of new cultivars for APSIM-Sugar under different environments, and show the effect of variation in climate on variation in parameter influence under different management conditions. It was confirmed that both radiation use efficiency and transpiration efficiency were sensitive and have to be examined to use new cultivars, though these are not listed as cultivar parameters.

Keywords: GEM-SA; apsimr; cultivar parameters; sugarcane; radiation use efficiency; transpiration efficiency; Sri Lanka; Japan

1. Introduction

The production of sugarcane is increasing in importance as both a food and a source of energy. Thus, productivity needs to improve continuously. The frequent introduction of new cultivars [1,2] and management strategies [3–5] around the world necessitates new studies to validate them. Several process-based crop models have been developed to simulate sugarcane growth and yield. The widely cited Agricultural Production Systems Simulator (APSIM)-Sugar model [6,7] and the Decision Support System for Agrotechnology Transfer (DSSAT)-Canegro model [8] can simulate the growth and yield of sugarcane under different environmental (climatic and soil) and management (irrigation, fertilization, etc.) conditions with different cultivars [2]. Crop models have been used for...
decision support in sugarcane farming, including irrigation scheduling [9,10], harvest scheduling [1,11], and fertilizer management [12]. They are also used in projecting the influence of climate change [13–15] and guiding varietal improvement [16]. However, most crop models are limited to old cultivars, so studies of varietal differences are limited [17]. Further, model based assessments of currently grown popular cultivars are still rare, for instance, no currently grown commercial cultivars are listed in APSIM-Sugar 7.10 [2]. Process-based crop models should be well parameterized and calibrated to achieve high accuracy. However, the measurement of a wide range of parameters is practically difficult, and not enough data are available from field experiments (including breeding trials) to parameterize all the required varietal information in APSIM-Sugar. Therefore, it is important to identify the most influential parameters in the simulation of outputs through sensitivity analysis (SA). Some parameters are easily measurable and available, whereas some are not, but they can be estimated through varietal calibration. SA can guide crop modelers in parameterizing their cultivars using available data and identify important parameters that need to be estimated by varietal calibration.

SA techniques can be broadly categorized as local or global [18]; local SA considers a single parameter at a time, and global SA considers the combined effect of multiple parameters. Saltelli and Annoni [19] reported the advantages of global SA over local SA; several global SA methods are available to estimate the sensitivity of process-based crop models to parameters, but they are computationally expensive. To minimize the computational cost, Sexton et al. [2] used an emulator-based approach to study the sensitivity of APSIM-Sugar to cultivar parameters. An emulator is a simplified statistical approximation of a more complex model [20] used in place of computationally expensive models. An emulator with a high enough accuracy can replace an actual simulator to perform SA [21]. In this approach, the simulator initially runs for relatively few simulations to build the emulator, then the emulator is used for the SA.

Here, we aimed at assessing the sensitivity of four yield outputs—total aboveground biomass, fresh cane weight, the weight of plant sucrose, and commercial cane sugar—to variations in 13 parameters used in APSIM-Sugar model under different environment and management conditions using emulator-based global sensitivity analysis. By assessing variations in the influence of parameters, we aimed at identifying important candidates for the parameterization and calibration of APSIM-Sugar in different environments and management conditions. We also investigated the effect of radiation use efficiency (RUE) and transpiration efficiency (TE) on the parameterization and calibration of APSIM-Sugar. The relationship between the variations in influence and climate is examined.

2. Materials and Methods

2.1. Study Area

Two locations with different climates were selected for this study: Itoman city (26°7′58″ N, 127°40′52″ E), Okinawa prefecture, Japan, and Sevanagala town (6°22′13″ N, 80°54′47″ E), Monaragala district, Sri Lanka. In Japan, Okinawa is the foremost cane sugar producer, accounting for about 59% of the country’s production. In the Köppen climate classification, Okinawa is classified as Cfa (humid subtropical) [22]. In Sri Lanka, sugar is an important subsector in the economy, with great potential for employment and income generation and for the development of the country’s dry zone. Sugarcane is grown mainly in the southern dry zone, where most processing plants are located. This zone of Sri Lanka is classified as As (tropical with dry summer) [23]. In Okinawa, the 30-year average monthly maximum and minimum temperatures both differ by about 15°C between summer and winter (Figure 1a). In Sri Lanka, they differ by only 2 to 3°C (Figure 1b). Solar radiation shows high seasonal variation in Okinawa (15 MJ/m²/day), but less variation (6 MJ/m²/day) in Sri Lanka. Average monthly rainfall shows a contrasting unimodal rainfall pattern in Okinawa but a bimodal pattern in Sri Lanka. The average monthly rainfall is 212 mm (± 72 mm SD) in Itoman and 169 mm (± 67) in Sri Lanka. APSIM uses the Priestley–Taylor method to estimate potential evapotranspiration (ET). The monthly potential ET varies slightly in Sri Lanka (2 mm/day) and moderately in Okinawa (4 mm/day; Figure 1).
Figure 1. Average monthly climate data of (a) Itoman, Okinawa, Japan (1980–2010) and (b) Sevanagala, Monaragala, Sri Lanka (1980–2010); rain, mean monthly rainfall (mm); radn, mean daily solar radiation (MJ/m²); maxt, mean daily maximum temperature (°C); mint, mean daily minimum temperature (°C); eo, Potential evapotranspiration (mm/day).

2.2. Apsim Simulation

APSIM is a process-based dynamic crop model that combines biophysical and management modules within a central engine to simulate diverse cropping systems [6,24]. The model is driven by daily climate data and can simulate the growth, development, and yield of crops and their interactions with soil.

APSIM-Sugar model simulates sugarcane growth via dry weight accumulation due to intercepted radiation in a daily time step. Dry weight accumulation in APSIM-Sugar is determined by RUE [7]. The model partitions the daily accumulated biomass into leaf, immature stem top, structural stem, roots, and sucrose. Then it simulates the key outputs (fresh cane yield, sugar yield, and sucrose contents) [2,7]. This process is controlled by environmental (soil and climate), plant or ratoon, and cultivar-specific parameters [7,25,26].

Sugarcane growth was simulated from 1 January 2000 to 31 December 2010, using rainfed conditions and irrigated conditions (assuming 50% management-allowed deficit). Soil data for Sri Lanka were derived using pedotransfer functions developed by Gunaratna et al. [27], and other data were gathered from a report by the Soil Science Society of Sri Lanka [28]. Soil data for Okinawa were collected through comprehensive soil analysis. Meteorological data for Sri Lanka were extracted from the AgMERRA global gridded climate dataset [29] by the NetCDF-Extractor v. 2.0 tool of AgriMetSoft (https://www.agrimetsoft.com). Those for Okinawa were obtained from the Japan Meteorological Agency website (http://www.data.jma.go.jp/gmd/risk/obsdl/index.php). In both locations, the data on daily rainfall, maximum temperature, minimum temperature, and solar radiation covered 1980 to 2010.

Figure 1 shows the variation of climatic variables used for these simulations. Table 1 summarizes the soil and management conditions of the two locations.

| Table 1. Soil and management conditions of selected locations used for the simulations. |
|---------------------------------|---------------------------------|---------------------------------|
| Location                        | Itoman, Okinawa, Japan          | Sevanagala, Monaragala, Sri Lanka |
| Soil                            | 26°7′58″N 127°40′52″E Shimajiri Mahji | 6°22′13"N 80°54′47″E Solodized Solonetz |
| Depth                           | 110 cm                          | 100 cm                          |
| PAWC                            | 68.4 mm                         | 91.6 mm                         |
| Planting                        | April 01 (Spring planting)      | April 01 (Yala season planting) |
| Crop duration                   | 315 days                        | 360 days                        |
| Stalk density                   | 7 stalks/m²                     | 8 stalks/m²                     |
| Fertilizer                      | 190 kg/ha as NH4-N              | 200 kg/ha as Urea               |
| Fertilizer application time     | 31 and 62 days after planting   | 45 and 90 days after planting   |
Table 1. Cont.

| Location                          | Itoman, Okinawa, Japan | Sevanagala, Monaragala, Sri Lanka |
|-----------------------------------|------------------------|-----------------------------------|
| **Irrigation**                    | Automatic irrigation   |                                    |
| **Fraction of ASW below which irrigation is applied** | = 0.5                  |                                    |
| **Efficiency of the irrigation**  | = 0.5                  |                                    |

PAWC, Plant available water content; ASW, Available soil water.

2.3. Gaussian Emulation Machine for Sensitivity Analysis (GEM-SA)

GEM-SA is an open-source software used to build software emulators from a set of inputs and outputs so as to perform predictions, uncertainty analysis, and SA using far fewer code runs than Monte Carlo–based methods [30]. It uses Bayesian analysis of computer code outputs [31]. The underlying mathematical procedures used in GEM-SA and analytical procedures used to conduct SA with GEM-SA are described in detail by Kennedy and O’Hagan [31], Kennedy et al. [32] and Kennedy and Petropoulos [30]. GEM-SA estimates two variance-based sensitivity indices—the main effect and the total effect—by partitioning the total output variance induced by variations in all input parameters [33]. Gunarathna et al. [34] reported the accuracy of emulators developed by GEM-SA for subtropical environments. Sexton et al. [2] used GEM-SA to assess the sensitivity of sugarcane biomass and yield to ten parameters in two regions in Australia; despite little variation in climate between the regions, sensitivities differed between the regions, as one region grows rainfed sugarcane and the other grows irrigated sugarcane. Gunarathna et al. [35] used GEM-SA to assess the sensitivity of outputs of APSIM-Oryza to soil parameters in different climatic conditions and reported different sensitivities among regions.

We used GEM-SA to assess the sensitivity of total (green + trash) aboveground biomass, fresh cane weight (canefw), the weight of plant sucrose (sucrose_wt), and commercial cane sugar (% ccs) to 13 selected parameters (Table 2). We assessed emulator accuracy, parameters that influence outputs, the variability of those parameters between years and between rainfed and irrigated conditions, and the effect of climate. Figure 2 shows an overview of the procedure we used for this study.

Table 2. Selected parameters used to assess the parameter sensitivity on total crop above-ground biomass, fresh cane weight, the weight of plant sucrose and commercial cane sugar.

| Parameter as Listed in APSIM-Sugar Model (Description) | Level | Code | Unit | Lower and Upper Bound |
|-------------------------------------------------------|-------|------|------|-----------------------|
| leaf_size (Leaf area of the respective leaf)          | Leaf_size_no = 1 | LS1  | mm²  | 500–2000              |
|                                                       | Leaf_size_no = 14| LS2  | mm²  | 25,000–70,000         |
|                                                       | Leaf_size_no = 20| LS3  | mm²  | 25,000–70,000         |
| cane_fraction (Fraction of accumulated biomass)       | CF    | g⁻¹  |      | 0.65–0.80             |
| partitioned to cane                                  |       |      |      |                       |
| sucrose_fraction_stalk (Fraction of accumulated)     | SF    | g⁻¹  |      | 0.50–0.70             |
| biomass partitioned to sucrose                       |       |      |      |                       |
| sucrose_delay (Sucrose accumulation delay)            | SD    | gm⁻² |      | 0–600                 |
| min_sstem_sucrose (Minimum stem biomass)             | MSS   | gm⁻² |      | 450–1500              |
| before partitioning to sucrose commences              |       |      |      |                       |
| min_sstem_sucrose_redn (reduction to minimum stem     | MSSR  | gm⁻² |      | 0–20                  |
| sucrose under stress)                                |       |      |      |                       |
| tt_emerg_to_begcane (Accumulated thermal time from    | EB    | °C day| 1200–1900 |
| emergence to beginning of cane)                      |       |      |      |                       |
| tt_begcane_to_flowering (Accumulated thermal time     | BF    | °C day| 5500–6500 |
| from beginning of cane to flowering)                 |       |      |      |                       |
| tt_flowering_to_crop_end (Accumulated thermal time    | FC    | °C day| 1750–2250 |
| from flowering to end of the crop)                   |       |      |      |                       |
| green_leaf_no (Maximum number of fully expanded green | GLN   | No.  | 9–14 |                       |
| leaves)                                              |       |      |      |                       |
Table 2. Cont.

| Parameter as Listed in APSIM-Sugar Model (Description) | Level | Code | Unit | Lower and Upper Bound |
|--------------------------------------------------------|-------|------|------|------------------------|
| Tiller_leaf_size (Tillering factors according to the leaf numbers) | Tiller_leaf_size_no = 1 | TLS1 | mm² mm⁻² | 1–6 |
| Tiller_leaf_size_no = 4 | TLS2 | mm² mm⁻² | 1–6 |
| Tiller_leaf_size_no = 10 | TLS3 | mm² mm⁻² | 1–6 |
| Tiller_leaf_size_no = 16 | TLS4 | mm² mm⁻² | 1–6 |
| Tiller_leaf_size_no = 26 | TLS5 | mm² mm⁻² | 1–6 |
| transp_eff (Transpiration efficiency) | Stage_code = 1 | TE1 | kg kPa/kg | 0.008–0.014 |
| Stage_code = 2 | TE2 | kg kPa/kg | 0.008–0.014 |
| Stage_code = 3 | TE3 | kg kPa/kg | 0.008–0.014 |
| Stage_code = 4 | TE4 | kg kPa/kg | 0.008–0.014 |
| Stage_code = 5 | TE5 | kg kPa/kg | 0.008–0.014 |
| Stage_code = 6 | TE6 | kg kPa/kg | 0.008–0.014 |
| rue (Radiation use efficiency) | Stage_code = 3 | RUE3 | g/MJ | 1.2–2.5 |
| Stage_code = 4 | RUE4 | g/MJ | 1.2–2.5 |
| Stage_code = 5 | RUE5 | g/MJ | 1.2–2.5 |

Figure 2. Flowchart of the analysis procedure used for the study.
2.4. Global Sensitivity Analysis

SA indicates which input parameters have the most influence on model outputs. We conducted SA using daily climate data from 2000 to 2010 to assess the sensitivity of the 4 yield outputs to 13 parameters (11 cultivar-specific parameters, RUE, and TE; Table 2) under rainfed and irrigated conditions in two distinct environments (Figure 2). Initially, 300 test points (of each and every parameter and outputs) evenly distributed between lower and upper bounds (Table 2) and related outputs of APSIM were generated by the apsimr package [36] of R software [37]. We chose the upper and lower bounds in consideration of the range of parameter values of cultivars in APSIM 7.10 Sugar model. We used the Gaussian Process emulator in GEM-SA [32] to develop 160 emulators (10 years \(\times\) 4 outputs \(\times\) 2 environments \(\times\) 2 management conditions). Variance based sensitivity indices (Main, \(S_i\) and total effects, \(ST_i\)) were estimated by partitioning the total output variance induced by variations in all input parameters with the assumption that all input uncertainties are unknown but uniform. The main effect index \((S_i)\) is defined as:

\[
S_i = \frac{\text{Var}[E(f(X|x_i))]}{\text{Var}[f(X)]}
\]

where, \(\text{Var}[f(X)]\) is the total variance in the output given variations in all parameters; \(\text{Var}[E(f(X|x_i))]\) is the variance in the expected output \(f(X)\) given \(x_i\) is known. Hence, \(S_i\) represents the expected reduction in output variance if parameter \(x_i\) were known [2]. The relative importance of each parameter in terms of its effect on output uncertainty can be ranked using this \(S_i\) values of selected parameters [38]. The total sensitivity index \((ST_i)\) is defined as:

\[
ST_i = 1 - \frac{\text{Var}[E(f(X|x_{-i})]}{\text{Var}[f(X)]}
\]

where, \(\text{Var}[E(f(X|x_{-i})]\) is the variance in the expected output \(f(X)\) if all parameters except \(x_i\) are known. Saltelli and Annoni [39] suggested to use \(ST_i\) when sensitivity analysis aims to set non-influential parameters to default values and removing them from potential calibrations.

The prior mean option for each input was set as linear. Models were assessed by using the leave-one-out cross-validation procedure of GEM-SA. In cross-validation procedure, a series of left-out points were estimated as output from the code which we actually know the true values. Therefore, the error values are readily available [40]. GEM-SA calculates the cross-validation root-mean-squared error (RMSE, Equation (3)) and root-mean-squared standardized error (RMSSE, Equation (4)) from the results of the cross-validation [30], and the sigma squared \((\sigma^2)\) value. We used these inbuilt diagnostics to assess the accuracy of the emulator approximations. We evaluated the variation in sensitivity of model outputs to changes in parameter values under two management conditions and two environments using the variances (as a percentage) of the main effect index \((S_i)\) and total effect index \((ST_i)\) provided by GEM-SA.

\[
\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (y_i - \hat{y})^2}{n}}
\]

\[
\text{RMSSE} = \sqrt{\frac{\sum_{i=1}^{n} ((y_i - \hat{y})/s_i)^2}{n}}
\]
3. Results and Discussion

3.1. Emulator Accuracy

A series of internally calculated statistical measures (\(\sigma^2\), RMSE and RMSSE) of GEM-SA were used to quantify the uncertainty of the sensitivity analysis due to emulation of model simulation [30]. We used \(\sigma^2\) (variance of the emulator after standardization of output) to evaluate the linearity of the GEM-SA emulators, as \(\sigma^2\) ranges near to 0 when a model shows linearity and show higher values when a model shows moderate to high nonlinearity, albeit with no defined cutoff values. Petropoulos et al. [41] reported that their emulators showed linearity or moderate nonlinearity at \(\sigma^2\) values between 0.13 and 1.6. We got \(\sigma^2\) values of 0.15 to 1.43 for Okinawa and 0.10 to 0.59 for Sri Lanka (Figure 3), so the models showed good to moderate linearity in both environments, and higher linearity in Sri Lankan conditions. Hence emulators can successfully replace the simulators.

RMSSE values are near 1 when emulator results are close to simulator results; lower and higher values respectively indicate over- and underestimation. Our RMSSE values of cross-validation results were close to 1: 0.89 to 1.09 in Okinawa and 0.85 to 1.12 in Sri Lanka (Figure 3). These values are lower than previously reported values of emulators assessed as satisfactory [30,41,42].

3.2. Sensitivity of Crop Growth and Yield to Changes in Plant and Cultivar Specific Parameters

Both main effect and total effect sensitivity indices of parameters varied significantly across environments and management conditions (Figures 4–7) and among years. There were no big differences between the main and total effect indices, and the main effect index was able to explain a major portion of the variability, so we neglected combined effects. Under rainfed conditions, soil moisture deficit is possible and may affect other processes. Thus, parameters showed less interannual variation under rainfed conditions than under irrigated conditions. Interannual variability was greater.
in Okinawa than in Sri Lanka as a result of wide variation in temperature and solar radiation during the growing season. We ranked the influence of parameters according to the median value of main effects over the 10 study years (Table 3). Significant contributions (over 1%) is highlighted (bold) in the Table 3.

Figure 4. Sensitivity of APSIM-Sugar biomass (g/m²) to parameters in (a) Okinawa and (b) Sri Lanka; Si, main effect; STi, total effect; IR, irrigated; RF, rainfed; TLS1-5, tiller leaf size; TE1-6, transpiration efficiency; SF2, sucrose fraction under stress; SD, sucrose delay; RUE3-5, radiation use efficiency; MSS, minimum structural stem sucrose; MSSR, MSS reduction; LS1-3, leaf size; GLN, green leaf number; FC, thermal time from flowering to crop end; EB, thermal time from emergence to beginning of cane; CF, cane fraction; BF, thermal time from beginning of cane to flowering.

RUE of growth stage 4 (from beginning of cane growth to flowering; RUE4) was the most influential on all the four tested model outputs despite locations and management (Table 3 and Figures 4–7). In both environments, biomass and cane fresh weight showed a different pattern of parameter influence from sucrose weight and ccs for all other parameters. RUE of growth stage 3 (from emergence to beginning of cane growth; RUE3) was the second most influential parameter for biomass and cane fresh weight. It was ranked two to three for CCS and sucrose weight in Okinawa and two to six for CCS and sucrose weight in Sri Lanka. For CCS and sucrose weight, MSS has a higher effect than RUE3. Green leaf number (GLN) was the third most influential parameter for biomass, and cane fresh weight, however, it was ranked four to five in Okinawa and three to five in Sri Lanka for CCS and sucrose.
weight. Cane fraction (CF) and thermal time between emergence and beginning of cane (EB) also influenced biomass in both environments in both water regimes.

Transpiration efficiency of growth stage 4 (TE4) has a greater influence in biomass under rainfed conditions than under irrigation conditions [43]. This was more pronounced under Sri Lankan growing conditions, probably because higher water-holding capacity of the Sri Lankan soil (Table 1). In both environments, minimum structural stem sucrose content (MSS) and sucrose fraction under stress (SF) influenced CCS and sucrose weight under both water regimes. CF also influenced CCS in both climates and sucrose weight in Sri Lanka under rainfed conditions. MSS reduction (MSSR) influenced ccs under rainfed conditions in Okinawa but not in Sri Lanka. Sexton et al. [2] reported higher sensitivity of biomass production to RUE and GLN and of sucrose yield to RUE and SF under Australian conditions.

In almost all cases, RUE4, RUE3, TE4 (plant-specific parameters), GLN, CF, MSS, and SF (cultivar-specific parameters) explained >90% of variability (Table 3). RUE4 had the greatest influence, and was more influential in Sri Lanka than in Okinawa in both water regimes. In both climates, growth stage 4 fell between July and the following February or March, when solar radiation, potential ET, and maximum and minimum temperatures varied much more in Okinawa than in Sri Lanka.

**Figure 5.** Sensitivity of APSIM-Sugar fresh cane yield (t/ha) to parameters in (a) Okinawa and (b) Sri Lanka. Si, main effect; STi, total effect; IR, irrigated; RF, rainfed. For parameter names, see Figure 4.
Figure 6. Sensitivity of APSIM-Sugar commercial cane sugar (%) to parameters in (a) Okinawa and (b) Sri Lanka. Si, main effect; STi, total effect; IR, irrigated; RF, rainfed. For parameter names, see Figure 4.
Figure 7. Sensitivity of APSIM-Sugar sucrose yield (g/m²) to parameters in (a) Okinawa and (b) Sri Lanka. S_i, main effect; ST_i, total effect; IR, irrigated; RF, rainfed. For parameter names, see Figure 4.

Table 3. Parameters most influential in simulation of biomass, canefw, ccs, and sucrose_wt in APSIM-Sugar under different environments (bold indicates parameters that contributed >1% of variation).

| Parameter | Biomass | Case Fresh Weight | CCS | Sucrose Weight |
|-----------|---------|-------------------|-----|---------------|
|           | RF      | IR                | RF  | IR            | RF  | IR            |
| Si Rank   | Si Rank | Si Rank           | Si Rank | Si Rank        | Si Rank | Si Rank        |
| Okinawa, Japan |       |                   |     |               |       |               |
| RUE4      | 49.0 1  | 57.7 1            | 58.3 1 | 66.3 1         | 41.2 1 | 42.3 1         |
| RUE3      | 18.0 2  | 23.6 2            | 12.6 2 | 17.2 2         | 5.4 3 | 7.0 3          |
| GLN       | 7.7 3   | 6.7 3             | 6.2 3 | 5.3 3          | 3.4 5 | 2.7 5          |
| CF        | 3.1 4   | 2.5 4             | 0.6 6 | 0.5 6          | 2.3 6 | 1.7 6          |
| TE4       | 1.7 5   | 0.5 5             | 6.0 6 | 0.5 5          | 0.1 10 | 0.0 11         |
| EB        | 1.4 6   | 1.8 5             | 1.0 5 | 0.5 4          | 0.2 8 | 0.2 8          |
| MSS       | 0.0 22  | 0.0 18            | 0.0 22 | 0.0 16         | 28.5 2 | 27.3 2         |
| MSSR      | 0.0 17  | 0.0 25            | 0.0 21 | 0.0 25         | 12.2 7 | 0.5 7          |
| SF        | 0.0 14  | 0.0 16            | 0.0 16 | 0.0 19         | 5.0 4 | 4.8 4          |
### Table 3. Cont.

| Parameter | Biomass | Cane Fresh Weight | CCS | Sucrose Weight |
|-----------|---------|-------------------|-----|----------------|
|           | RF      | IR                | RF  | IR             |
| Si Rank   | Si Rank | Si Rank           | Si Rank | Si Rank |
| Monaragala, Sri Lanka |
| RUE4      | 60.5    | 71.1              | 1   | 76.4           |
| RUE3      | 14.5    | 13.0              | 2   | 13.1           |
| GLN       | 6.7     | 6.2               | 3   | 5.7            |
| CF        | 5.3     | 3.7               | 4   | 0.7            |
| TE4       | 6.0     | 1.4               | 6   | 1.4            |
| EB        | 1.5     | 1.6               | 5   | 0.5            |
| MSS       | 0.0     | 18.0              | 0.0 | 23.0           |
| MSSR      | 0.0     | 16.0              | 12  | 21.0           |
| SF        | 0.0     | 23.0              | 8   | 26.0           |

Biomass, total aboveground biomass (g/m²); Cane fresh weight (t/ha); CCS, commercial cane sugar (%); sucrose weight (g/m²); RF, rainfed; IR, irrigated; Si, main effect; RUE, radiation use efficiency; GLN, green leaf number; CF, cane fraction; TE, transpiration efficiency; EB, thermal time from emergence to beginning of cane; MSS, minimum structural stem sucrose; MSSR, MSS reduction; SF, sucrose fraction under stress.

#### 3.3. Role of RUE4 on APSIM-Sugar Simulations

Daily dry matter production (DDMP; g/m²) of sugarcane under irrigated conditions was simulated using the default values for RUE (1.8 g/MJ) and TE (8.7 g/kPa/kg) in APSIM-Sugar. Maximum possible daily dry matter production (MDMP; g/m²) was calculated as the product of daily intercepted solar radiation and RUE. APSIM estimates intercepted solar radiation as a function of leaf area index and radiation extinction coefficient of 0.38 (Equation (5)).

\[
I = I_0 \times \exp(-k \times LAI)
\]  

where, \(I\) is the Intercepted solar radiation, \(I_0\) is the total solar radiation at top of the canopy, \(k\) is extinction coefficient and \(LAI\) is the leaf area index.

During growth stage 4, DDMP had a close relationship with solar radiation in both environments (Figure 8), confirming the high dependency of DDMP on solar radiation. However, it had greater uncertainty throughout the range of intercepted solar radiation in Okinawa than in Sri Lanka, indicating limitation by other factors. This explains the higher sensitivity of DDMP to RUE4 in Sri Lanka. RUE is highly sensitive to nitrogen stress and to high and low temperatures [44]. No nitrogen stress was reported during this period in either environment (see the next paragraph). Therefore, temperature and solar radiation contributed most to the variation in the sensitivity of DDMP to RUE4 in both environments.

Lower DDMP values than MDMP values confirm that APSIM-Sugar did not use the maximum RUE values to simulate DDMP during growth stage 4 specially in days with higher intercepted solar radiation (Figure 9c). During the study period, the minimum and maximum temperatures were within the optimum range (15–45 °C, Figure 9a) [45], and no nitrogen deficit and only slight water stress were recorded (Figure 9b). There was no water stress on days with a radiation level of <15 MJ/m² (Figure 9d), and APSIM-Sugar operates with maximum RUE. RUE can be maximized with favorable water, nitrogen, and temperature conditions [44], and some authors reported higher RUE values than 2 g/MJ [46–48] while APSIM-Sugar remains at 1.8 g/MJ. This might cause APSIM to underestimate yield, especially in simulation studies based on modern commercial sugarcane cultivars.
Sexton et al. [2] found high interannual variation of parameter influence and suggested the contribution of climatic variation. Several plant- and cultivar-specific parameters showed

Since RUE is a standard parameter in plant and ratoon crops, it is usually unchanged in varietal parameterization. However, cultivars show a range of RUE values [48], so it needs to be parameterized to achieve good simulations. Sexton et al. [2,49] suggested to add RUE and TE as varietal parameters
in upcoming APSIM versions; our results prompt us to agree. Our results under Okinawan conditions are similar to those reported by Sexton et al. [2], but there are no published results to compare with the Sri Lankan environment. Therefore, we suggest the need for studies to determine the influence of sugarcane cultivar parameters in different tropical environments to confirm our findings. Sexton et al. [49] reported the inability of APSIM-Sugar to differentiate the yields of four commercial cultivars. The lack of enough cultivar parameters that influence the growth and yield of sugarcane means that APSIM-Sugar may not be able to distinguish varietal differences if those parameters are not parameterized and calibrated properly.

3.4. Investigation of Interannual Variation in Parameter Influence

Sexton et al. [2] found high interannual variation of parameter influence and suggested the contribution of climatic variation. Several plant- and cultivar-specific parameters showed considerable interannual variation in influence (Figures 4–7). To study the influence of climatic parameters on interannual variation in sensitivity in Sri Lanka, we investigated the sensitivity of canefw to highly influential parameters (Table 3). Considering climatic factors, we selected three growing seasons (Y2 2001–02, Y7 2006–07, Y10 2009–10) for comparison (Figure 10). We calculated cumulative growing degree-days, assuming a base temperature of 9 °C. Y10 had the highest cumulative growing degree-days (6663) and Y7 had the lowest (6425). Y7 had the highest cumulative rainfall (2232 mm) and Y2 had the lowest (1504 mm). Y2 had the highest cumulative solar radiation (6703 MJ/m²) and cumulative potential ET (1688 mm). Y10 had the lowest cumulative solar radiation (6179 MJ/m²) and cumulative potential ET (1566 mm).

As a tropical country, Sri Lanka receives high solar radiation even in high-rainfall years. Therefore, under irrigated conditions, canefw had high sensitivity to RUE4 in all three years. Since irrigation supplies all crop water requirements, RUE4 had greater influence in Y2, a low-rainfall year with high solar radiation, than in the other years. Under rainfed conditions, RUE4 had a stronger relationship to canefw in Y7 (highest rainfall) than in the other years. This result confirms the higher sensitivity of
canefw to RUE4, but the sensitivity is directly linked to moisture availability for plants. Solar radiation was similar among years in the first 3 months of the growing season but then differed among years. Under irrigated conditions, the sensitivity of canefw to RUE3 was similar among years. Under rainfed conditions, however, it was less in Y2 than in the other years. In Y2, RUE3 became insensitive to increasing RUE as controlled by soil moisture deficit due to less rainfall and high potential ET. Under irrigated conditions, GLN, TE4, CF, and EB showed little or no variation in influence among years. Under rainfed conditions, however, GLN, TE4, and CF showed greater variation in influence, more so in Y2, owing to both higher solar radiation and moisture stress.

To study the influence of climatic parameters on interannual variation in sensitivity in Okinawa, we selected three growing seasons (Y2 2001–2002, Y4 2003–2004, and Y9 2008–2009) for comparison (Figure 11). Y4 had the highest cumulative growing degree-days (4847) and Y2 had the lowest (4833). Since Okinawa receives high rainfall due to typhoons, the cumulative rainfall does not reflect cropping conditions, so we calculated the effective rainfall by using a water balance approach. Y2 had the highest cumulative rainfall (2478 mm) and Y9 had the lowest (1215 mm), but Y4 had the highest cumulative effective rainfall and Y2 had the lowest. Y9 had the highest cumulative solar radiation (4999 MJ/m²) and cumulative potential ET (1247 mm). Y2 had the lowest cumulative solar radiation (4690 MJ/m²) and cumulative potential ET (1170 mm).

![Figure 11](https://example.com/figure11.png)

**Figure 11.** Depiction of interannual sensitivity variation of sugarcane in Okinawa: cumulative rainfall (mm), cumulative effective rainfall (mm), cumulative solar radiation (MJ/m²), cumulative growing degree-days, cumulative potential evapotranspiration (mm), and parameter sensitivity variation among 2001–2002, 2003–2004, and 2008–2009.

With lower solar radiation than in Sri Lanka, the sensitivity of canefw to RUE4 was lower, but still significant, in Okinawa in all three years. The sensitivity of canefw to RUE4 was lowest in Y2 owing to the lower solar radiation and effective rainfall than in the other two years. Under the lower solar radiation, the influence of RUE4 differed little between irrigated and rainfed conditions. This result confirms the higher sensitivity of canefw to RUE4, but the sensitivity is directly linked to solar radiation and moisture availability for plants. RUE3 also showed less influence on canefw in Y2 than in the other two years, on account of lower effective rainfall and solar radiation. Although the climatic conditions were similar, under rainfed conditions canefw was less sensitive to RUE3 in Y4 than in Y9. Canefw was more sensitive to GLN in Y4 and Y9 than in Y2 owing to higher effective rainfall and solar
radiation. TE4, CF, and EB had little or no variation in influence among years under either irrigated or rainfed conditions.

3.5. Relationship between Statistical Dispersion and Climatological Parameters

We examined the statistical dispersion of emulator canefw outputs in response to climatic parameters (Figure 12). In Sri Lanka, under irrigated conditions, cumulative solar radiation (CSR) had the closest relationship with the average output, and cumulative growing degree-days had the closest relationship with SD. Under rainfed conditions, cumulative rainfall had the closest relationship with average and CSR had the closest relationship with SD. In Okinawa, under both water regimes, CSR had the closest relationship with average and SD.

Figure 12. Relationships between average and SD of emulator canefw predictions with most closely related climatic conditions during the study period.

Solar radiation is a key factor governing the sensitivity of canefw to parameters irrespective of climatic conditions. Under high solar radiation with abundant soil moisture, canefw depended mainly on solar radiation, and its variability in sensitivity depended on temperature. Under high solar radiation with water stress, canefw depended mainly on rainfall, and its variability in sensitivity was governed mainly by solar radiation. Under low solar radiation, irrespective of water availability, canefw and its sensitivity were governed mainly by solar radiation. Similarly, Grossi et al. [50] reported the higher sensitivity of sorghum yield to rainfall, solar radiation, and CO2 in DSSAT simulations. Hence, solar radiation, rainfall, and temperature have the greatest influence on canefw in crop models.

4. Conclusions

We used GEM-SA to assess the influence of 13 parameters (11 cultivar-specific parameters, RUE, and TE) of APSIM-Sugar on predicted biomass, fresh cane yield, sucrose weight, and commercial cane sugar yield (ccs) under rainfed and irrigated conditions in two distinctive environments. In both environments, all four outputs were highly sensitive to the RUE of crop growth stage 4 (from the beginning of cane growth to flowering) and growth stage 3 (from emergence to the beginning of cane growth) and to green leaf number, irrespective of water regime. Biomass was sensitive to cane fraction and thermal time from emergence to the beginning of cane (EB) in both environments. In Okinawa, biomass and fresh cane yield were sensitive to TE of growth stage 4 under rainfed conditions, but less sensitive under irrigated conditions. In Sri Lanka, they were sensitive under both water regimes. In both environments, ccs and sucrose weight were sensitive to minimum structural stem sucrose content (MSS) and sucrose fraction under stress condition (SF) under both water regimes. In
Okinawa, ccs and sucrose weight were slightly sensitive to MSS reduction (MSSR) and cane fraction under rainfed but less sensitive under irrigated conditions. In Sri Lanka, biomass, fresh cane yield, and sucrose yield were sensitive to TE of growth stage 4 under rainfed but less sensitive under irrigated conditions. These results confirm distinct variations in parameter influence across climates, management conditions, and outputs. This shows why SA conducted in similar environments is vital to identifying parameters important for parameterization and calibration of sugarcane cultivars. In both environments, green leaf number and cane fraction were important candidates for parameterization of cultivars. We suggest that attention to calibration of EB, MSS, MSSR, and SF will improve the accuracy of simulations of sugarcane growth and yield in both environments. Although they are not listed as cultivar parameters in the APSIM-Sugar model, if reliable and ample data available, it is advisable to calibrate TE of growth stage 4 and RUE of growth stages 3 and 4 also. Interannual variations in solar radiation, rainfall, and temperature explained the variation of parameter influence. Therefore, variations in climatic parameters must be accounted for in the modeling of sugarcane growth and yield using APSIM.

Author Contributions: M.H.J.P.G., K.S. and M.K.N.K conceptualized, conceived and performed, and K.S., T.N. and K.M. supervised the study. M.H.J.P.G. and K.S. interpreted data and developed the manuscript. All authors read and approved the final manuscript.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

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