MODELING OF THE OPTIMIZED SUBSURFACE IRRIGATION SYSTEM (OPSIS) WITH APSIM-SUGAR AND ASSESSING THE APPLICABILITY OF OPSIS TO SRI LANKAN CONDITIONS

地下灌漑システム OPSIS の APSIM-Sugar を用いたモデルかと OPSIS のスリランカへの適用性の検討

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ABSTRACT

M.H.J.P. Gunarathna, 2019, Modeling of the optimized subsurface irrigation system (OPSIS) with APSIM-Sugar and assessing the applicability of OPSIS to Sri Lankan conditions, Doctor of Philosophy Thesis in Regional Resource Environment Engineering, The United Graduate School of Agricultural Sciences-Kagoshima University.

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Climate change threatens the sustainability of most rainfed sugarcane farming systems. Hence, rainfed sugarcane farming systems are gradually being replaced by irrigated farming systems wherever such transition is possible. Also, low-efficiency irrigation systems are being replaced by high-efficiency systems to make sugarcane farming more economically sustainable. However, irrigation is one of the most expensive practices of sugarcane farming systems. Therefore dimensions of sugarcane irrigation systems need to be adjusted for water conservation while simultaneously reducing operational costs.

The optimized subsurface irrigation system (OPSIS) is a subsurface irrigation system for irrigating the root zone of upland crops by capillarity. In design, OPSIS can significantly reduce percolation losses, which are common problems in other subsurface irrigation systems. Because a small solar-powered pump is used to lift water and create a pressure head and because minimum operational activities are required, OPSIS offers the potential to lower the operational costs of irrigation for sugarcane farmers drastically.

Agricultural Production Systems sIMulator (APSIM) is widely using crop model with numerous uses, including the evaluation of different irrigation management practices. Proper parameterization, calibration, and validation are essential in achieving the success of simulations using crop models. Hence developing simulation capabilities with developed technologies is vital to get the maximum benefit for the development of crops and new management strategies.

This study aimed to develop OPSIS as a user-friendly, economically viable, and environmental sound irrigation method for upland farmers worldwide. Specifically, this study aimed to, 1) to introduce and scientifically validate the newly developed optimized subsurface irrigation system (OPSIS); 2) to enhance modeling capability of Agricultural

Production Systems sIMulator (APSIM) to use with OPSIS; 3) to study the applicability of OPSIS for tropical environments.

We conducted field experiments representing all planting conditions (spring and summer planting, main and ratoon crops) to compare the performances of OPSIS over sprinkler irrigation. This study showed that OPSIS offers advantages over sprinkler irrigation for sugarcane cultivation in Okinawa in respect of both sugarcane yield and WUE. Compared with sprinkler irrigation, OPSIS produced significantly taller plants, and thus significantly longer millable stalks, and significantly more millable stalks. Therefore, OPSIS achieved significantly higher fresh cane weight using less irrigation water than did sprinkler irrigation. OPSIS is a water-conserving irrigation technique that can irrigate sugarcane crops with minimal operational cost, energy consumption, and human intervention. Therefore, it may be a sustainable alternative for sugarcane crop irrigation in Okinawa and similar subtropical environments.

We parameterized and calibrated the APSIM-Sugar model to simulate growth and yield of sugarcane cultivar Ni21 under Okinawan conditions, then, validated the APSIM to use with OPSIS. We developed APSIM-OPSIS module to couple OPSIS with APSIM engine. Simulated plant height and fresh cane yield showed good agreement with the observations. However, APSIM showed overestimation for soil water content in upper soil layers and irrigation water use of OPSIS. Hence, it is concluded that the newly developed APSIM-OPSIS module can successfully be used to simulate the crop growth and yield of sugarcane with optimized subsurface irrigation system.

We parameterized and calibrated the APSIM-Sugar model to simulate growth and yield of Sri Lankan local sugarcane cultivar SL96128. Then we simulated the growth and yield of sugarcane under rainfed, surface irrigated, and OPSIS irrigated conditions for two locations in Sri Lanka with distinct soils. Results revealed that in both soils OPSIS performed better than the rainfed and surface irrigation; however the performance of OPSIS is remarkable with clay loam soil. Hence, it is concluded that the OPSIS can significantly increase the crop growth and sugarcane under Sri Lankan conditions, especially in the places with clayey soils. With future climates, APSIM may perform better than the surface irrigation and rainfed conditions. The design modification may require achieving expected performances of OPSIS under sandy soil conditions.

Keywords: APSIM, crop modeling, GEM-SA, Japan, OPSIS, pedotransfer functions, sensitivity analysis, Sri Lanka, subsurface irrigation, sugarcane, WEKA

要約

OPSIS は畑作において、根群域に灌漑するシステムである。OPSIS は他の地下灌漑システムで問題となる下方浸透を少なくすることが可能である。OPSIS は、太陽光パネルを電源としてポンプ操作をするため、農家の操作コストを大幅に減らすことが可能である。APSIM は、広く利用されている作物モデルであり、違った灌漑操作の評価ができる。作物モデルを適切に使うには、パラメータの決定・同定および検証が重要である。従って、開発された技術のシミュレーション手法の開発は、その技術の利用効果を最大限にするためには不可欠である。そこで、本研究では、OPSIS を利用しやすく、経済的で環境に優しい灌漑システムとして開発することを目的とした。具体的には、1) OPSIS の紹介および科学的検証 2)OPSIS の APSIM を用いたモデル化 3)OPSIS の熱帯環境での適用性検討、である。

沖縄県でのすべての栽培条件での OPSIS とスプリンクラー灌漑の比較実験を行なった。その結果、OPSIS はスプリンクラー灌漑に比べて、収量と水利用効率において有効であった。OPSIS 利用条件では、作物高さ、茎長および茎数に関して高い値となった。これにより、OPSIS 利用条件では、スプリンクラー灌漑より少ない水量で高い収量を得ることができた。OPSIS はサトウキビ栽培において少ない管理コストおよびエネルギーで灌漑できる水保全型の灌漑方法である。従って、OPSIS は沖縄や亜熱帯地域のサトウキビ栽培において持続的な手法になりうると考える。

我々は、沖縄県の条件で農林 21 号のシミュレーションのために ASSIM-Sugar のキャリブレーションを行い、APSIM を用いた OPSIS のモデル化の検証を行なった。APSIM に OPSIS の機能を取り込み APSIM-OPSIS モジュールを開発した。適用では、作物高さと生茎重の計算において実測値の再現ができた。しかし、APSIM では土壌水分の計算に関して過大評価する結果となった。

次に、スリランカの品種に対して APSIM-Sugar のパラメータ同定を行なった。そして、無灌漑、地表灌漑および OPSIS 条件で 2 地点の土壌データを用いてシミュレーションを行った。その結果、どちらの土壌条件でも OPSIS 条件では天水および地表灌漑より収量がよくなる計算結果となった。特に、粘土性の土壌ではその効果が顕著である計算結

果となった。これらの計算結果から、OPSIS はスリランカにおいても有用である可能性があることが示唆された。

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LIST OF ABBREVIATIONS

AgMERRA	AgMIP climate forcing dataset based on the NASA modern-era retrospective analysis for research and applications
AIC	Akaike information criterion
APSIM	Agricultural production systems simulator
ASW	Available soil water
BD	Bulk density
BF	Thermal time from the beginning of cane to flowering
canefw	Fresh cane weight
CCC	Lin's concordance correlation coefficient
CCS	Commercial cane sugar
CF	Cane fraction
CL	Clay
CMIP5	Coupled Model Intercomparison Project Phase 5
CS	Coarse sand
CSR	Cumulative solar radiation
d	Wilmott's agreement index
DDMP	Daily dry matter production
DSSAT	Decision support system for agrotechnology transfer
DUL	Drainage upper limit
EB	The thermal time between emergence and beginning of cane
ET	Evapotranspiration
FAO	Food and agriculture organization
FC	Thermal time from flowering to crop end
FS	Fine sand
GCMs	Global climate models
GEM-SA	Gaussian emulation machine for sensitivity analysis
GLN	Green leaf number
IGP	Indo-Gangetic Plain
IPCC	Intergovernmental panel on climate change
IR	Irrigated
IWUE	Irrigation water use efficiency
k	Extinction coefficient
KS	Saturated hydraulic conductivity
LAI	Leaf area index
LL15	Drainage lower limit
LSD	Least significant difference
MAE	mean absolute error
Max.T	Maximum temperature
MCS	Medium coarse sand
MDMP	Maximum possible daily dry matter production
Min.T	Minimum temperature
MJ	Megajoule
MLR	Multiple linear regression
MSS	Minimum structural stem sucrose content

MSSR	Minimum structural stem sucrose reduction
NH4-N	Ammonium nitrogen
NO3-N	Nitrate nitrogen
OC	Organic carbon
OPSIS	Optimized subsurface irrigation
P	Probability
PAWC	Plant available water content
PTFs	Pedotransfer functions
PVC	Polyvinyl chloride
R^2	Coefficient of determination
RAE	Relative absolute error
RCPs	Representative concentration pathways
RF	Rainfed
RGP	Reduced growth phenomenon
RMSE	Root mean squared error
RMSSE	Root mean squared standardized error
RRSE	Root relative squared error
RUE	Radiation use efficiency
SA	Sensitivity analysis
SA	Sand
SAT	Soil saturation
SD	Standard deviation
SD	Sucrose delay
SF	Sucrose fraction under stress
Si	Main effects
SI	Silt
SR	Solar radiation
ST	Soil texture
STi	Total effects
sucrose_wt	Weight of plant sucrose
SW	Soil water
TD	Particle density
TE	Transpiration efficiency
TLS	Tiller leaf size
USDA	United States Department of Agriculture
VCS	Very coarse sand
VFS	Very-fine sand
VWC	Volumetric water content
WEKA	Waikato environment for knowledge analysis
WUE	Water use efficiency

1.0 General Introduction

The sustainability of rainfed agriculture in some regions is in peril as it gravely threatened by climate change. Hence not only the food security but also the social structure in many countries is in danger as rainfed agriculture occupies 80% of the world's agricultural lands and currently contributes 60% of the world's food production. Therefore, urgent attention to developing water management strategies and irrigation facilities is required; however, still, it is one of the significant contributors to operational costs in agriculture. Hence, the adaptation could inhibit by the reluctance of farmers to adopt practices that elevate operational costs. Therefore, new technologies would be more likely to be taken if they were designed to save precious water resources and at the same time, keep associated labor and energy costs as low as possible.

Climate change threatens the sustainability of most rainfed sugarcane farming systems (Knox et al., 2010). It may harm the sugarcane growth and yield if no appropriate irrigation facilities introduce (Zhao and Li, 2015). Rainfed sugarcane farming systems are gradually being replaced by irrigated farming systems wherever such transition is possible. Also, low-efficiency irrigation systems are being replaced by high-efficiency systems to make sugarcane farming more economically sustainable. However, irrigation is one of the most expensive practices of sugarcane farming systems; the dimensions of sugarcane irrigation systems need to be adjusted for water conservation while simultaneously reducing operational costs.

The optimized subsurface irrigation system (OPSIS) is a subsurface irrigation system for irrigating the root zone of upland crops by capillarity. In design, OPSIS can significantly reduce percolation losses, which are common problems in other subsurface irrigation systems. Because a small solar-powered pump is used to lift water and create a pressure head and because minimum operational activities are required, OPSIS offers the potential to lower the operational costs of irrigation for sugarcane farmers drastically. OPSIS is still new and has had little uptake as there is not yet sufficient information on it, therefore needs to be compared with other irrigation methods regarding both yield performances and water conservation. OPSIS would be a new avenue of sugarcane irrigation for resource-limited environments. Therefore, OPSIS could be an economically sustainable irrigation option for sugarcane farmers in areas where the resources are limited.

A crop simulation model is a vital tool with numerous uses, including the evaluation of different irrigation management practices. Further, it is an essential tool to assess the effectiveness of new technologies as it can evaluate the latest technologies with minimum effort on field trials, hence fewer resources. Proper parameterization, calibration, and validation are essential in achieving the success of simulations using crop models. Agricultural Production Systems sIMulator (APSIM) is widely using crop model which focus on simulating crop resource supply rather than crop resource demand. It provides a good understanding of the long-term sustainability of cropping practices and management strategies (Gaydon et al., 2017). APSIM is diversely evaluated in Australia and Africa but not in Asia. The existing few attempts were also mainly focused on crops like rice, wheat, and maize (Gaydon et al., 2017). Hence developing simulation capabilities with developed technologies is vital to get the maximum benefit for the development of crops and new management strategies.

Crop and environmental modeling hinder by limited data availability. Hence it is essential to develop methodologies to generate required data for crop modeling using available data. Pedotransfer functions (PTFs) are predictive functions which are used estimate soil parameters (which are difficult to measure) using some easily measurable soil parameters (Bouma, 1989). Though it is not advisable to extrapolate PTFs, PTFs developed for temperate soils are extensively using in tropical regions due to limited availability of appropriate PTFs and/or most software are using PTFs developed for temperate soils as their default (Minasny and Hartemink, 2011; Patil and Singh, 2016; Tomasella and Hodnett, 2004).

1.1 Objectives of the study

This study aimed to develop OPSIS as a user-friendly, economically viable, and environmental sound irrigation method for upland farmers worldwide. Specifically, this study aimed to,

1) To introduce and scientifically validate the newly developed, optimized subsurface irrigation system (OPSIS).
2) To enhance modeling capability of Agricultural Production Systems sIMulator (APSIM) to use with OPSIS
3) To study the applicability of OPSIS for tropical environments.

1.2 Outline of the work plan and dissertation

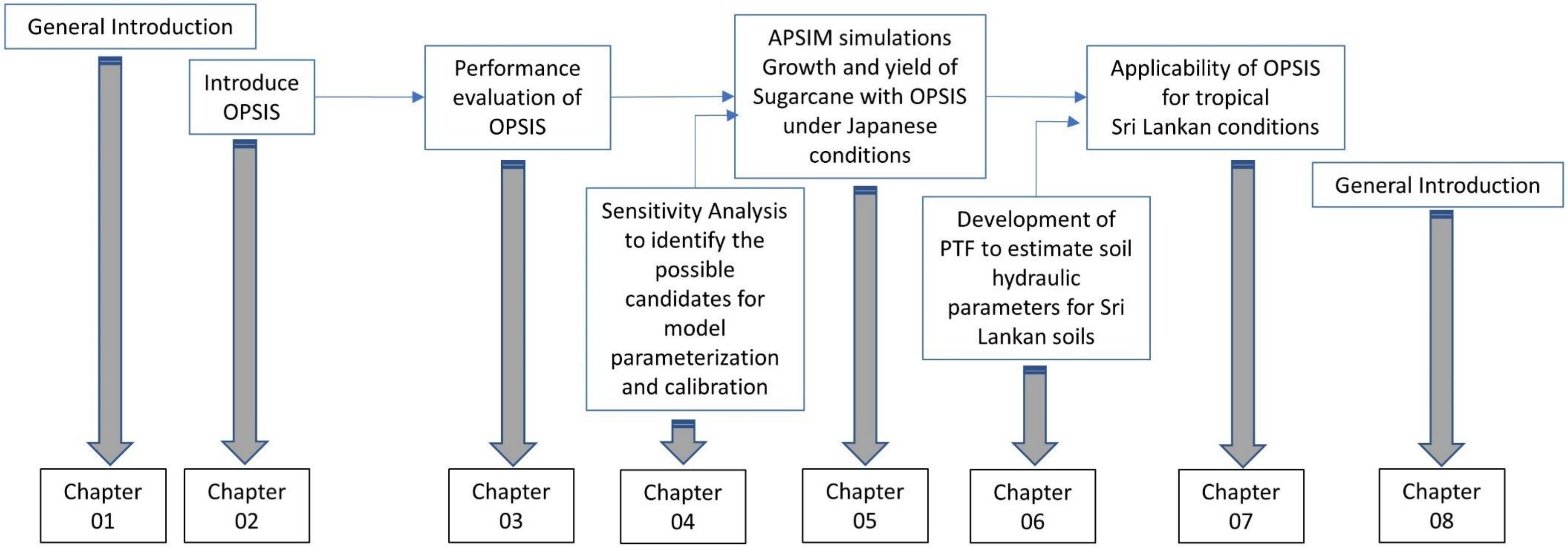

Figure 1.1. Outline of research work and the dissertation

1.3 References

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2.0 Optimized Subsurface Irrigation System (OPSIS)

This chapter is based on Gunarathna, M.H.J.P., Sakai, K., Nakandakari, T., Kazuro, M., Onodera, T., Kaneshiro, H., Uehara, H., Wakasugi, K., 2017. Optimized Subsurface Irrigation System (OPSIS): Beyond Traditional Subsurface Irrigation. Water 9, 599. https://doi.org/10.3390/w9080599

2.1. Introduction

Rainfed agriculture occupies 80% of the world's agricultural lands and currently contributes 60% of the world's food production (FAO, 2011). However, the sustainability of rainfed agriculture in some regions is in peril as it is gravely threatened by climate change (IPCC, 2014), as a result of which not only food security (Webber et al., 2014) but also the social structure (Roudier et al., 2011) in many countries is in danger. Since water availability directly influences the efficient use of all other inputs, better water availability, in turn, ensures optimum yields from a given combination of inputs (Sharma et al., 2015). Therefore, emerging irrigation technologies ideally should be developed to enhance crop water availability to make agricultural practices sustainable in the long run. Although shifting from rainfed to irrigated agriculture or from low-efficiency to high-efficiency irrigation methods offers necessary remedial measures against a changing climate, adaptation could be inhibited by the reluctance of farmers to adopt practices that elevate operational costs, such as high-efficiency irrigation methods. Therefore, new irrigation technologies would be more likely to be adopted if they were designed to save precious water resources and at the same time, keep associated labor and energy costs down to the lowest extent possible.

Various irrigation methods, such as surface, subsurface, sprinkler, and drip irrigation, can be used to irrigate upland crops. The method selected would depend on physical, economic, and social factors, and in turn, determines the efficiency of resource use, economic viability, and sustainability of upland farming systems (Ali, 2011). Since earlier times, surface irrigation methods such as basins, borders, furrows were used to irrigate upland crops in many regions of the world, owing to its simplicity and low cost. In surface irrigation methods, water flows over the entire field or along furrows by gravity. When flowing, water infiltrates to the soil, and it provides irrigation water to the root zone of crops. The uniformity of distribution and application efficiency depends on the degree of land leveling; therefore it consumes high labor cost for land preparation (Strelkoff and Clemmens, 2007; van Lier et al., 1999). With increasing energy and labor costs, however, and with increasing demand for diminishing water resources, surface irrigation has been replaced to some extent by subsurface, sprinkler, or drip irrigation methods. However, it still is the major irrigation method used to irrigate upland crops worldwide. Drip and sprinkler irrigation methods were developed for high-frequency irrigation of crops using a systematically installed pipe network and emitting devices (Ali, 2011; Martin and Heermann, 2007). In drip and sprinkler systems, water is supplied under pressure and water often passes through various types of filters depending on the type of irrigation system and water source (Martin and Heermann, 2007). Sprinkler irrigation including solid sets, periodic move or continuous move systems, traveling guns and boom sprinkler systems, has advantages over surface irrigation in terms of its high efficiency of water application, ease of fertilizer application, and high resultant crop yields (Mikkelsen et al., 2015). However, it also has some drawbacks such as high setup costs, high operational costs due to its high energy requirements and maintenance, and its tendency to be adversely affected by wind conditions (van Lier et al., 1999). Drip irrigation (irrigation systems are designed to slowly apply water to individual points) on the other hand, overcomes some of these drawbacks by way of low energy requirements and not being affected by the wind. It has distinctive water and energy-saving features while supporting the agronomy of crops to address the challenges facing irrigated agriculture (Evans et al., 2007). However, it may perform poorly with crops that have high water requirements. The major drawback in drip irrigation systems is the clogging of emitters, which leads to poor performance and calls for frequent maintenance. Further, damage by weathering and farm machinery partly explains why such an appealing technology remains unpopular among farmers (Ali, 2011; Mikkelsen et al., 2015; van Lier et al., 1999). Although subsurface drip irrigation (application of water below the soil surface by drip emitters) systems have been developed to overcome the prevailing practical issues of drip irrigation, they have not performed as expected, since they further aggravate the problem of poor water distribution efficiency due to emitter clogging (F. R. Lamm et al., 2013; Jiusheng Li et al., 2008; Payero et al., 2005).

2.1.1 Objectives of the study

A new irrigation method is being developed to irrigate upland crops which aim to use water more efficiently and effectively while minimizing costs to improve profitability and sustainability. In this regard, it is essential to minimize significant water losses through evaporation, surface runoff, and percolation in order to economize on the limited availability of water, while also driving down the labor and energy requirements and keeping operational costs to a minimum. Therefore, any new design should be able to ensure (i) high application efficiency with uniform distribution, (ii) low capital investment, (iii) low energy and labor requirements to minimize operational costs, (iv) automated operation with minimum supervision, (v) minimum influence from weather, topography, or soil type, (vi) minimum disturbance to other management practices, and (vii) environmentally friendly technology.

2.1.1. Optimized subsurface irrigation system (OPSIS)

The capillarity, upward water movement in a tube due to cohesion, adhesion, and surface tension forces can also happen in soil. In soils, water can move upwards through soil pore spaces between soil particles. The height of capillary rise is dependent on pore sizes as smaller the soil pores show higher the capillary rise. Our newly developed "optimized subsurface irrigation system" (OPSIS) is designed to irrigate upland crops using capillarity of soil. Water releases by perforated pipe just below the root zone and water move upward due to capillarity of soil to irrigate the crops. Subsurface irrigation methods perform better in soils that are vulnerable to drought damage (soils with low available water), and hence OPSIS shows better results than other irrigation methods in such environmental contexts. OPSIS shows super water-saving capability as it can minimize runoff, evaporation, and percolation. Since only a small solar-powered pump is used to make the elevation head, OPSIS does not incur any ongoing energy costs, and since it can operate with minimal labor as an automated system, it should drastically bring down the operational costs of irrigation.

2.2. Technical details of OPSIS

In OPSIS, water is elevated using a solar-powered submersible pump to create an elevation head to a higher level and, then it flows along with the gravity. Subsurface perforated pipe leak water while flowing by gravity, then soil capillarity provides the irrigation water to the crops. OPSIS consists of a main water control unit and a water distribution system (Figure 2.1). After a series of laboratory and field experiments on irrigation amount, water distribution and cost-effectiveness under local soil conditions in Okinawa dimensions and materials of construction of each part have determined.

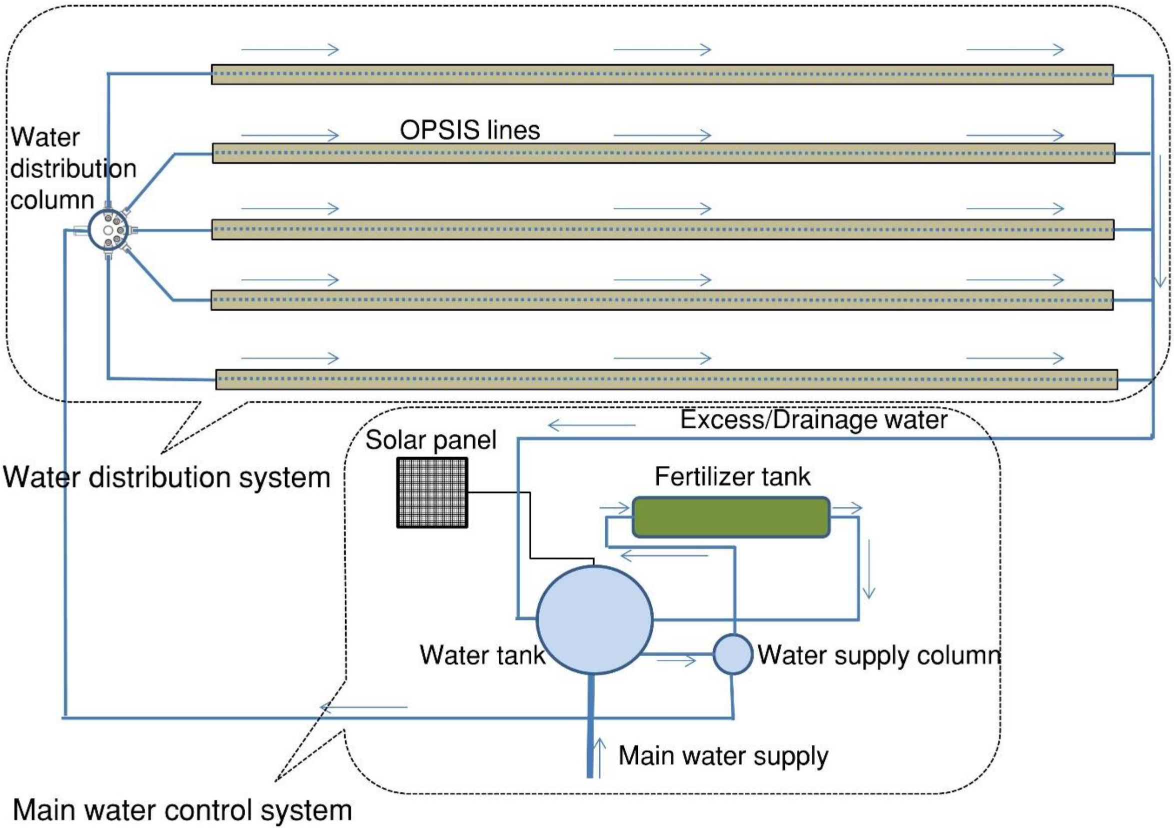

Figure 2.1. Schematic diagram of OPSIS

2.2.1. The main water control system

The main water control system includes a water tank to store water temporarily, a solar pump to elevate the water, a water supply column to control the water flow, and a fertilizer tank to facilitate fertigation. It regulates both the quantity and the pressure of all water coming into the irrigation system and provides controlled water and fertilizer flow out to the water distribution system.

2.2.1.1. Water tank

The size of the water tank (Figure 2.2) varies according to the source of water and the requirements of the farmer. The supply of water, such as from an irrigation canal or groundwater, is regulated by a ball tap. Because of the head difference between the water tank and the field, excess water from the OPSIS lines and drainage water from the field flows back to the water tank. A solar-powered submersible pump is used to pump the water out from the tank and into the water supply column.

2.2.1.2. Water supply column

The water supply column (Figure 2.3) provides a controlled and constant flow of water and fertilizer into the water distribution system. A constant water level is maintained in the column using a drainage tube attached to it. The pressure and volume of water discharged to the water distribution system are controlled by a micro tubing mechanism in the column. A thin tube wrapped around the center pipe sends the water smoothly and slowly into the outlet of the water column. The volume of the discharge depends on the water height in the column, and can, therefore, be controlled by adjusting the height of the drainage tube. The water column also connects to the fertilizer tank and provides a controlled flow of water to the water distribution column through an underground pipe.

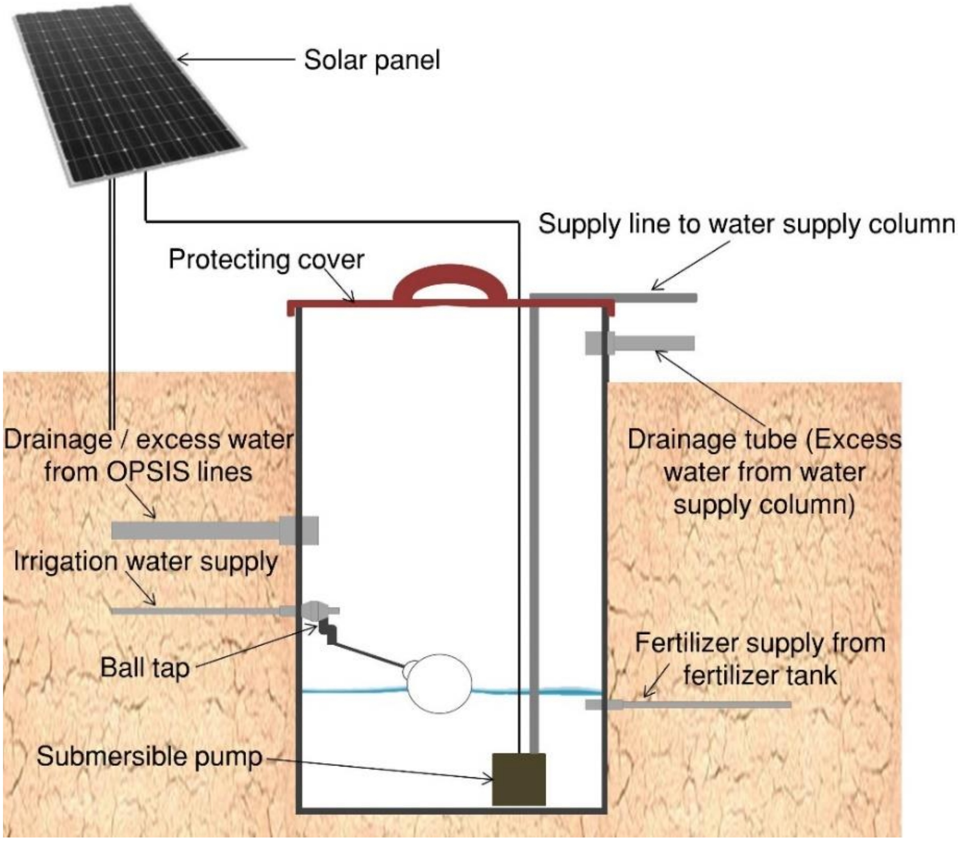

Figure 2.2. Schematic diagram of the water tank

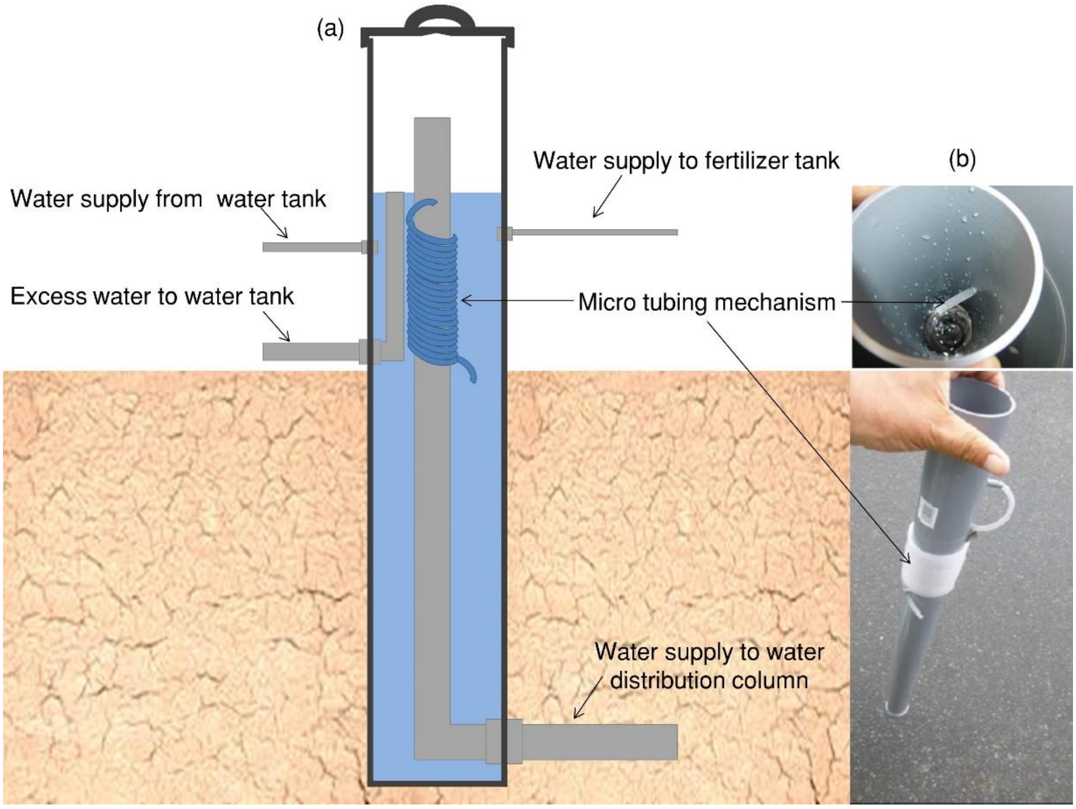

Figure 2.3. Water supply column a) Schematic diagram of water supply column b) Use of micro tubing mechanism

2.2.1.3. Fertilizer tank

Fertilizer dissolved in water is added to a compressible bag inside the fertilizer tank. The water fed by the water column creates pressure inside the fertilizer tank, which compresses the bag and thus releases the fertilizer at very low rates into the irrigation system (Figure 2.4).

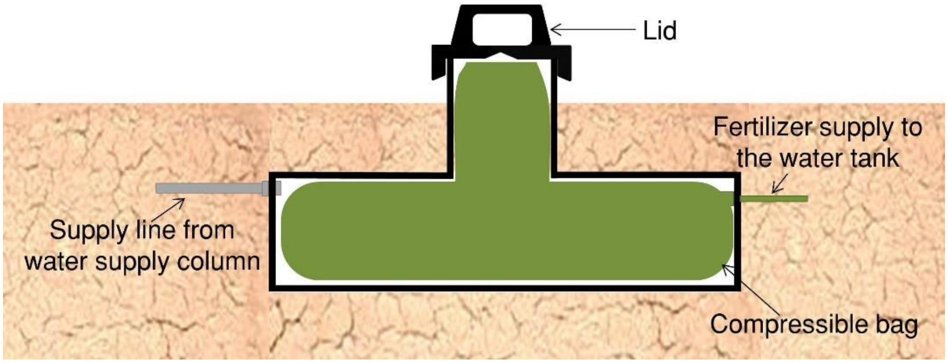

Figure 2.4. Schematic diagram of fertilizer tank

2.2.2. Water distribution system

The water distribution system is the part responsible for distributing the irrigation water equally over the field. It includes a water distribution column at the head end of the field that distributes the water equally among the OPSIS lines, polyvinyl chloride (PVC) or metal sheet to control percolation, and perforated pipes buried horizontally under the field surface to irrigate the field.

2.2.2.1. Water distribution column

The water distribution column (Figure 2.5) distributes water to 5-7 perforated pipes (OPSIS lines) buried below the soil surface. The mechanism in the water distribution column allows water to be distributed equally to all OPSIS lines despite any irregularities in the land. Equal distribution of water to all OPSIS lines is ensured by having the same height of water in the discharge tubes. When several water distribution columns are used on slopes, the equal distribution of water can be ensured by adjusting the discharge tubes in all water distribution columns to be at the same level (Figure 2.6).

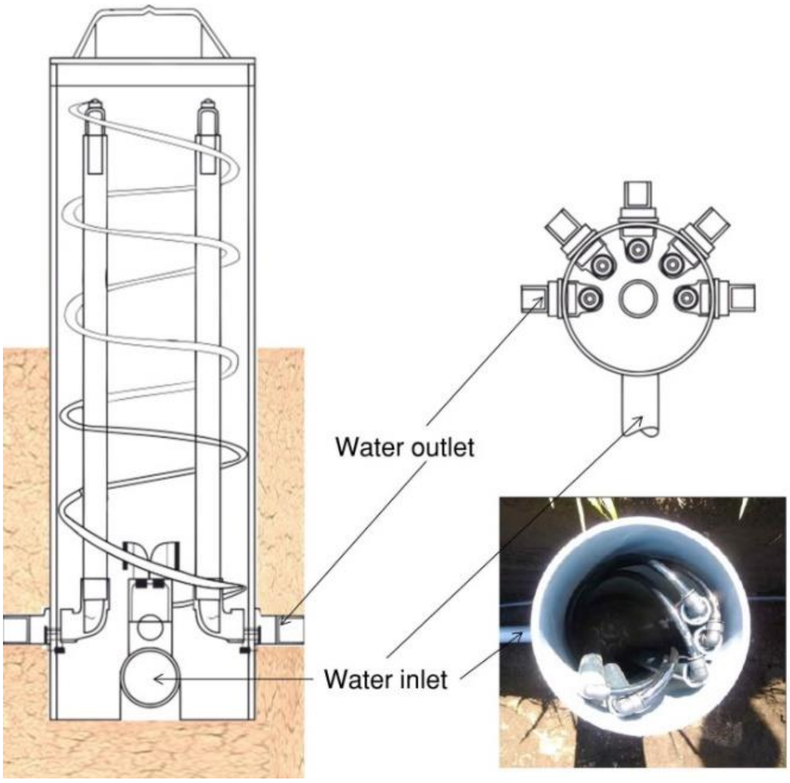

Figure 2.5. Schematic diagram of water distribution column of OPSIS

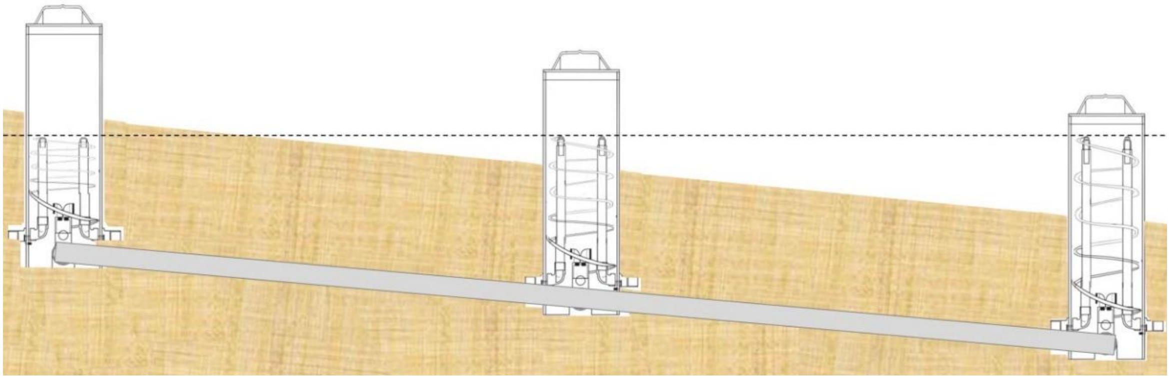

Figure 2.6. OPSIS can ensure equal discharge on sloping land

2.2.2.2. Perforated OPSIS lines

Perforated 50-mm pipes release the water. When OPSIS is operating, water flows under gravity along the pipes. As the water advances, it can move to the outside soil, depending on the water potential. As water moves outside, the soil becomes saturated. After that, the water potential of the outside soil and inside of the pipe reaches equilibrium. This equilibrium controls the amount and rate of irrigation. Further, the water starts to move upward from the saturated layer owing to the water potential created by matrix effects such as capillary action created via surface tension. As water moves upward, the moisture content of root zone soil increases and provides irrigation water to the crop. For crops planted in rows, the spacing of the OPSIS lines could be maintained to match the row spacing. In sandy soils, closer OPSIS lines would be preferred, whereas, in clayey soils, much wider spacing may be used. However, field and laboratory experiments on water distribution confirmed that it is advisable to maintain a distance of about 1–3 m between two OPSIS lines according to the soil type and crop spacing to ensure an even water supply for all crops while minimizing costs and water losses. Field and laboratory experiments on water distribution, workability condition and possible damages by tillage equipment confirmed that the depth of the lines could vary between 30 and 60 cm according to the soil type and the root zone depth.

A waterproof PVC or metal sheet can be used to control percolation losses. The sheet is buried in an inverted trapezoidal shape (Figure 2.7). Ability to control percolation losses, the effect on crop yield and availability of materials were considered when determining the size and shape of the PVC or metal sheet to control percolation losses. After a series of field and laboratory experiments, the minimum optimum height to minimize the percolation was identified as 15 cm. Therefore, the optimum size of the shape has been determined to be 12 cm wide at the base, 30 cm wide at the top, and 15 cm high considering the prices of materials available in the market. The perforated pipe is positioned in the center of the shape.

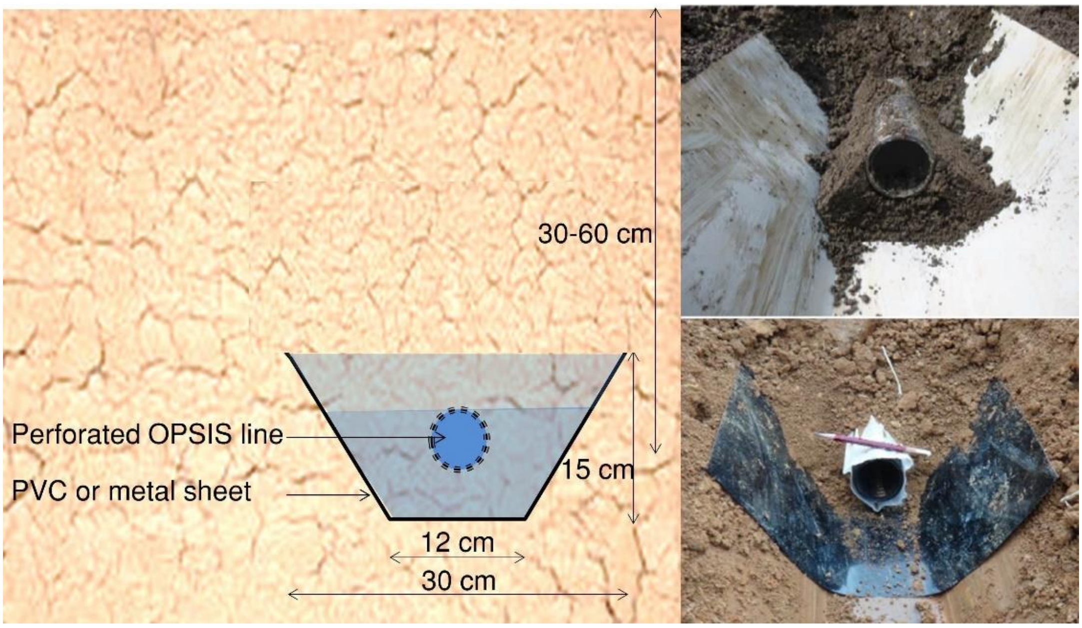

Figure 2.7. Use of PVC or metal sheet to control percolation losses

2.2.3. OPSIS can act as a drainage system

During the rainy season (when OPSIS might not operate, owing to low solar radiation) the water in the saturated soil can enter the perforated pipes following the water potential gradient. As water is circulating, the tail-end water collects in the drainage pipe and is diverted to the water tank. Thus, OPSIS could act as a subsurface drainage system during rainy periods.

Figure 2.8 shows the daily rainfall, irrigation or drainage by OPSIS, and level of soil saturation (percent of water-filled volume to the total porosity of the soil) in the root zone area of experiment field, Itoman, Okinawa, Japan during July 2014. The irrigation or drainage axis shows the net amount of water that goes out of (positive values) or comes into (negative values) the water tank. Positive values represent the irrigation, while negative values show the amount of drainage. The level of soil saturation (%) in the root zone area of each day was calculated using daily soil moisture (volume basis) and soil porosity. It shows that OPSIS can manage soil moisture content at desirable levels even in very high rainfall seasons such as shown in Figure 2.8, where rainfall was 832 mm per month including a maximum daily rainfall of 350 mm.

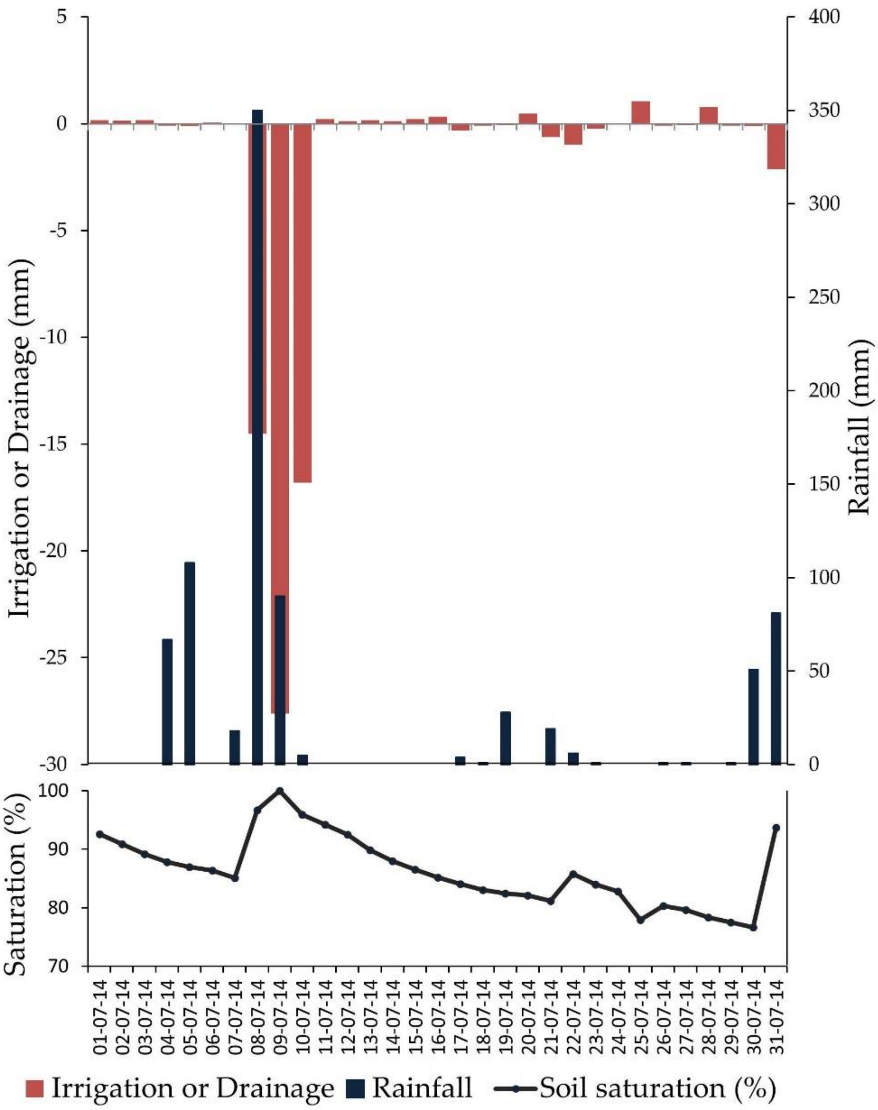

Figure 2.8. Variation in rainfall, irrigation/drainage, and percentage of soil moisture saturation

2.2.4. System Installation

The significant component of OPSIS installation is the laying out of the perforated OPSIS lines. Initially, this was done by digging with a conventional excavator with a bucket. Since this is time-consuming and expensive, an attachment was developed to layout the system more efficiently and effectively. The attachment can layout both the pipe and the sheet simultaneously, thus drastically cutting down the cost and time of installation while significantly improving the workability and accuracy of the system layout. The attachment is being developed to further reduce the initial establishment cost and accuracy of the system layout (Figure 2.9).

Figure 2.9. Installation of OPSIS lines a) Manually laying out lines, b) Use of a machine to layout the lines

2.2.5. Field Testing of OPSIS

Field experiments were set to examine the optimum depth of installation, the optimum number of OPSIS lines per water distribution column, possible length of OPSIS lines. Further, growth and yield performances of Sugarcane, maize, and soybean with OPSIS were tested in different parts of Japan. Some key results showed that maize and soybean with OPSIS reported 40 and 50% higher yields respectively compared to the surface irrigation methods. Field experiments conducted during 2012 - 2014 to study the performances of OPSIS showed that OPSIS increased the fresh cane yield by 79-116% compared to the rainfed conditions as attributed by higher plant height, cane diameter and a higher number of millable stalks per unit area. Figure 2.10 and 2.11 shows the growth and yield performances of sugarcane with OPSIS compared to the rainfed conditions.

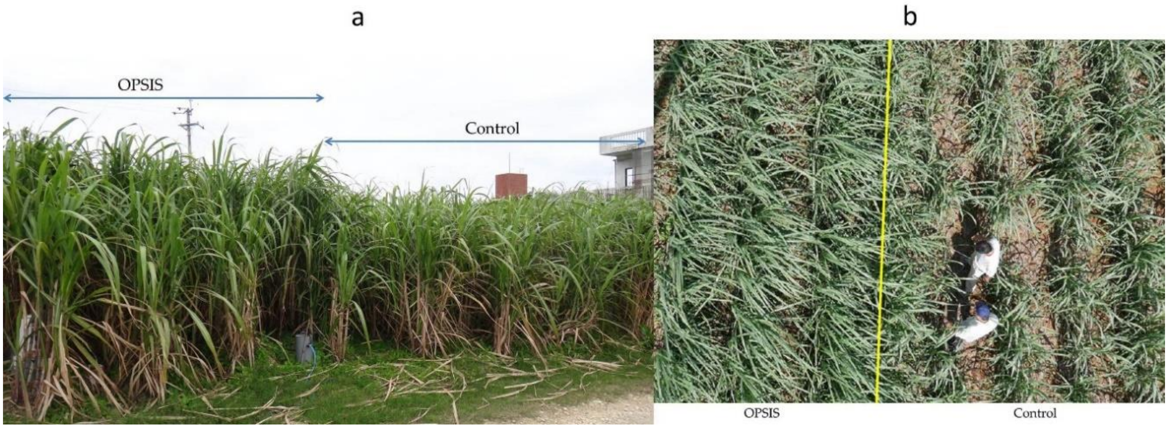

Figure 2.10. Growth of sugarcane with OPSIS and rainfed condition a) Plant height, b) Canopy cover

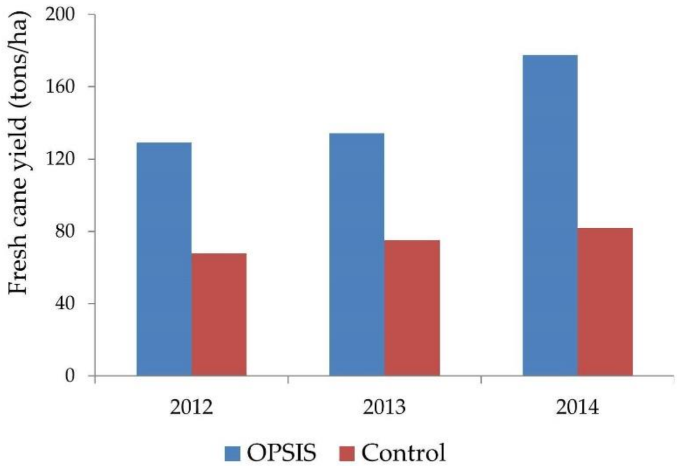

Figure 2.11. Fresh cane yield of sugarcane with OPSIS and rainfed condition

2.3. Results and Discussion

2.3.1. Special Features of OPSIS

Series of field and laboratory experiments were carried out to examine the performances of OPSIS. Based on the results, observations, and experiences, following unique features of OPSIS were identified.

2.3.1.1. Water-saving irrigation method

OPSIS shows improved water-saving capability compared with other irrigation methods as it can function with minimum percolation, evaporation, and surface runoff.

2.3.1.2. Ensures uniform water distribution

OPSIS can be used on slopes where surface irrigation is not suitable. It requires less attention to land leveling than surface irrigation methods, and it is better than other irrigation methods in achieving equal distribution of irrigation water on slopes.

2.3.1.3. Ensures good crop yields

Field experiments conducted in different places in Japan using sugarcane, maize, and soybeans as test crops confirmed the high yields obtained with OPSIS compared with other irrigation methods.

2.3.1.4. Ensures sanitary field conditions

Since the surface layer remains dry, OPSIS it provides optimum workability conditions and allows the maintenance of sanitation in the field. The dry state of the topsoil helps to maintain excellent workability and creates low humidity, especially in protected greenhouses. No topsoil splattering or erosion hazards occur, as there are no surface water droplets or flowing water with OPSIS.

2.3.1.5. Enables fertigation

Water-soluble fertilizers can be effectively used with the irrigation water with OPSIS. The slow-release nature ensures higher fertilizer use efficiency than can be achieved under other fertigation or fertilizer application methods.

2.3.1.6. Minimal operational costs

OPSIS is powered by solar energy, and therefore, it has no real energy costs. As an automatic system, it also requires minimum human supervision for irrigation during the cropping season. As a subsurface system, it causes minimal disturbance to other field operations. Further, it does not require comprehensive land leveling. Therefore, OPSIS has the lowest operational costs of all irrigation methods.

2.3.1.7. No clogging

No large debris can enter to water distribution system as water has to pass the microtube in water supply column. As an open-ended system, OPSIS do not experience negative pressures inside the lines nor soil ingestion when stopping the system as which usually happen in subsurface drip irrigation systems.

2.3.1.8. Long durability

Once OPSIS is installed, it can be used for years without any need for re-installation because there is no damage by sunlight, animals, or farm machinery.

2.3.1.9. Drainage system

OPSIS can act as a subsurface drainage system. Therefore, no separate drainage system is required for water management in fields in which OPSIS is installed.

2.3.1.10. Environmentally friendly technology

Being a solar-powered irrigation system, OPSIS does not consume any fossil fuels. As a subsurface fertigation system, it emits fewer greenhouse gases than with the surface application of fertilizers or fertigation. Further, owing to minimum percolation losses and the slow release of fertilizer, OPSIS helps to minimize the contamination of groundwater with fertilizer.

2.3.2. Limitations of OPSIS

Installation of OPSIS requires a considerable initial cost. However, factors such as no need for a separate drainage system, high crop yields, minimum operational costs, and long durability can help recover the high initial cost of installation within few years. As some percolation losses are inevitable, losses of fertilizer can happen with OPSIS. After the installation of the system, deep plowing will be impossible as it can damage the system. Therefore, to the extent possible, care should be taken to avoid the development of a hardpan, and suitable machinery that can break up the hardpan should be used only with utmost care.

2.4. Recommendations

Although OPSIS is commercially available for sugarcane farmers in Okinawa, Japan, it needs the validation of its performance and further improvement to make it a more highly efficient and low-cost irrigation method. Further, to help farmers operate OPSIS with minimal problems and to make irrigation more profitable and sustainable, guidelines for best management practices need to be developed and introduced.

Installation of OPSIS requires a considerable initial investment; therefore, new strategies and technologies should be developed to minimize the initial cost.

OPSIS provides irrigation water to the field automatically whenever there is solar radiation available to operate the pump. This can lead to some percolation losses, especially during dry periods and in fields with low groundwater levels or sandy soil. Changing the automatic operational mechanism to one that adjusts the pump according to soil moisture by incorporating soil moisture sensors could be helpful to reduce percolation losses further and maximize the lifespan of the pump.

The optimum depth at which to install the perforated OPSIS pipes may vary depending on the soil type, crop to be grown, and depth to the groundwater table. Since OPSIS has been tested with only a limited number of crops and soil types, further studies should be carried out under different soil and climate conditions with different crops.

Patterns of root distribution that develop with subsurface irrigation systems might differ from those that develop with other irrigation systems. Therefore, studies focused on root distribution and soil moisture extraction patterns might be helpful for further development of OPSIS.

It might be challenging to break the hardpan after installing the OPSIS. Therefore, new technologies or strategies might have to be developed to minimize the creation of hardpans and to break them without damaging the OPSIS lines.

OPSIS is tested only for small and medium scale fields in Japan. The maximum length of the OPSIS lines tested is less than 100 m. Therefore, the applicability of large scale fields yet to be examined.

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3.0 OPSIS for Sugarcane Irrigation

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3.1. Introduction

Sugarcane (*Saccharum officinarum* L.) is one of the most important crops in the world. It plays a vital economic role in sugar and bioenergy production and has an essential social role in the rural communities of sugar-producing nations worldwide.

Climate change threatens the sustainability of most rainfed sugarcane farming systems (Knox et al., 2010). Some authors have reported that the climate change may harm sugarcane growth and yield without the introduction of appropriate irrigation facilities (Carvalho et al., 2015; Knox et al., 2010; Varella et al., 2012; Zhao and Li, 2015). Rainfed sugarcane farming systems are being gradually replaced by irrigated farming systems wherever such transition is possible. Also, low-efficiency irrigation systems are being replaced by high-efficiency systems to make sugarcane farming more economically sustainable. However, irrigation is one of the most expensive practices of sugarcane farming systems and can account for more than 25% of the production cost (Mazibuko et al., 2002; Narayanamoorthy, 2005). Therefore, the dimensions of sugarcane irrigation systems need to be adjusted toward water conservation while simultaneously reducing operational costs.

Although sugarcane can tolerate some moisture stress, it still has a high-water requirement, in the range of 1500 to 2500 mm per season (Brouwer and Heibloem, 1986) required to achieve yields close to the potential maximum (Inman-Bamber and Smith, 2005; Shukla and Lal, 2003). Most importantly, sugarcane requires an evenly distributed water supply throughout its growing season to produce high yields. Even though sugarcane requires a high-water supply, it is also susceptible to waterlogging, which reduces plant growth and yield (Skocaj et al., 2013). Therefore, to maintain optimum soil moisture throughout the growing period and achieve close to maximum yields, both appropriate irrigation and drainage facilities are vital in sugarcane fields.

Freshwater is often a scarce resource, and sugarcane faces competition from other water uses; therefore, irrigation systems should be able to use water efficiently. However, if the water is free or priced too low, farmers have no incentive to adopt capital-intensive technologies unless they confer other benefits (e.g., lower energy and labor costs, higher nutrient use efficiency).

Surface, overhead, and drip irrigation methods are most commonly used to irrigate sugarcane crops (Carr and Knox, 2011), depending on physical characteristics, economic considerations, and social and other considerations. The performance of irrigation systems directly affects crop performance, water use efficiency (WUE), cost of production, and profit and is, therefore, of keen interest to farmers (Mudima, 2000)

The same irrigation method and the same amount of water can produce significant differences in yield with different patterns of water application. Therefore, more uniform irrigation application needs to be targeted through design, continuous evaluation, and maintenance practices (Lecler and Jumman, 2009). However, continuous evaluation and maintenance require farmers to invest time and money that they may not have.

Traditionally, most sugarcane farming systems used surface (specifical furrow) irrigation because of its simplicity and low cost. However, the increasing cost of energy and labor and increasing demand for scarce water resources has led to greater adoption of overhead or drip irrigation methods. However, furrow irrigation is still the dominant method used worldwide (McGuire et al., 2010). The significant drawbacks of furrow irrigation and the main reasons for its unpopularity among sugarcane farmers are the high labor requirement and low WUE stemming from percolation and tail-water losses (McGuire et al., 2010; Narayanamoorthy, 2005). Furrow irrigation is remarkably less efficient in light-textured soils than overhead and drip irrigation systems. Although measures such as the use of low flow rates (Torres et al., 2010), surge irrigation (McGuire et al., 2010; Young et al., 2006), and local modifications (El-Berry et al., 2006) can increase the efficiency of furrow irrigation to a degree, such refinements have not been able to achieve satisfactory levels of efficiency and do not obviate the high labor requirement.

Sprinkler and drip irrigation methods utilize water pressure to irrigate sugarcane crops. A comparative study of surface drip irrigation, subsurface drip irrigation, and surface irrigation of sugarcane reported that both surface and subsurface drip irrigation systems performed as well as surface irrigation systems in a few key areas such as plant growth and development and water savings (Hanafy et al., 2008). Pires et al. (2012) reported a higher fresh cane yield under subsurface drip irrigation than under rainfed farming. Shinde and Deshmukh (2007) reported similar sugarcane yields from drip and rain gun sprinkler methods that exceeded those of surface irrigation, but rain gun sprinkler irrigation consumed 33% more water than drip irrigation, which also gave a more uniform water distribution. In a comparison of different hydrant pressures (4.0, 4.5 and 5.0 bars) and nozzle sizes (2.4 mm × 4.4 mm and 2.4 mm × 4.8 mm), Dinka (2016) reported large deep percolation losses (about 40%) in sprinkler irrigation in Ethiopia. It is a waste of water resources, energy, and soluble nutrients, which results in increased production costs and environmental impacts.

Subsurface drip irrigation enhances growth and yield not only through the precise application of the right amount of water but also by maintaining adequate aeration of the root zone. Further, it promotes the effectiveness of applied fertilizers by minimizing losses through processes such as denitrification, deep percolation, and runoff, which can occur with other irrigation methods. The optimum depth of subsurface drip lines varies between 10 and 80 cm depending on the soil type, soil depth, and crop type, as capillary action ensures water uptake by upward water movement. With the same amount of water, subsurface drip irrigation wets an area about 50% larger than surface drip irrigation does. Mahesh et al. (2016) reported that subsurface and surface drip irrigation could save 31% and 23% of water relative to surface irrigation. They further reported significantly higher sugarcane yield and WUE with subsurface fertigation than with surface irrigation with conventional fertilizer application. However, subsurface drip irrigation entails some drawbacks, such as low germination if there is poor capillary movement, salinity, nozzle clogging, and uneven water distribution (Kaushal et al., 2012). Moreover, it does not always assure high efficiency and good yield because it requires a perfect design and a skilled operator (Dlamini, 2005). Therefore, new methods or strategies must be introduced to subsurface irrigation systems to achieve better precision while overcoming the inherent disadvantages of available subsurface irrigation methods.

Okinawa prefecture, Japan, comprises many small islands with little or no surface water resources; therefore, sugarcane farming there requires water-efficient irrigation methods. However, drip irrigation, the most water-efficient method available, is not widespread among sugarcane farmers in the prefecture because it is labor-intensive and requires frequent monitoring, and many farmers are aged and favor low-maintenance farming systems. Therefore, water-saving irrigation methods that can be operated with minimum attention is required to make sugarcane farming systems in Okinawa more sustainable and economically viable.

The optimized subsurface irrigation system (OPSIS) is a new subsurface irrigation system for irrigating upland crops. It irrigates the root zone of the crop by capillarity (Gunarathna et al., 2017). OPSIS has two major components: a main water control system (including a solar-powered submersible pump, a water tank, a water supply column, and a fertilizer tank) and a water distribution system (including a water distribution column at the head end of the field, perforated pipes buried parallel to the field surface to irrigate the field and PVC or metal sheet to control seepage losses). Similar to the other subsurface irrigation systems, OPSIS is remarkable for its ability to eliminate surface runoff and evaporation (Gunarathna et al., 2017). Further, it significantly reduces percolation losses, which are common problems in other subsurface irrigation systems (Gunarathna et al., 2017). Because a small solar-powered pump is used to lift water and create a pressure head, and minimum operational activities are required (Gunarathna et al., 2017), OPSIS offers the potential to drastically lower the operational costs of irrigation for sugarcane farmers in Okinawa.

In OPSIS, water flow is automatically triggered by solar radiation (as it uses a solar-powered pump), without any manual operation. However, it irrigates (emits water through perforated pipes) based on the soil moisture potential difference between the inside of the pipe and outside soil. Further, it can remain in place during other field operations, including mechanical harvesting (Gunarathna et al., 2017). In that respect, OPSIS is compatible with the low-intervention requirements of Okinawan sugarcane farmers. Further, as the farmers irrigate their fields prescriptively (set timing and amounts), rainfall that occurs shortly after scheduled irrigation application leads to water wastage, whereas OPSIS irrigates only when required. However, OPSIS is still new and has had little uptake in Okinawa as no sufficient information yet.

3.1.1. Objectives of this study

To compare OPSIS with sprinkler irrigation in terms of both yield performances and water conservation.

3.2. Materials and Methods

3.2.1. Field experiment

Field experiments were conducted in Itoman, Okinawa, Japan (26° 7' 59.07" N, 127° 40' 52.32" E) during 2013–2016 to compare the performances of OPSIS and sprinkler irrigation in sugarcane cultivation under subtropical conditions. The climate of the Itoman area is classified as Cfa by the Köppen classification system (Rubel and Kottek, 2010) and generally refer to as subtropical, with dry summers and mild cold winters. Climatic data of Naha, Okinawa (26° 12' 26" N, 127° 41' 11" E) were gathered from Japan meteorological agency to assess the climatic conditions in Itoman during the study periods (Table 3.1).

However, daily rainfall of the experimental field was also measured to the precise calculation of water use efficiency of irrigation treatments. Soil present in the experimental site is generally known as dark red soils, called Shimajiri-Maji, which correspond to Udalfs, Udepts, and Udolls in the USDA Soil Taxonomy (Kubotera, 2006).

The sugarcane cultivar Ni21 used for this experiment is a Japanese cultivar that was developed to withstand strong winds from typhoons. The single-row planting method with 1.3 m spacing between rows was used in all treatments.

Experiments were conducted to observe growth and yield under two planting conditions, namely spring planting and summer planting as a local practice in Okinawa. Spring-planted sugarcane crop was extended to observe the growth and yield of two consecutive ratoon crops. In Okinawa, summer planting usually starts in September and spring planting in March. Both crops are harvested from January to March according to the requirement of sugarcane millers. Table 3.1 shows the planting and harvesting times of the crops studied. Figure 3.1 shows the field layout of the experiment.

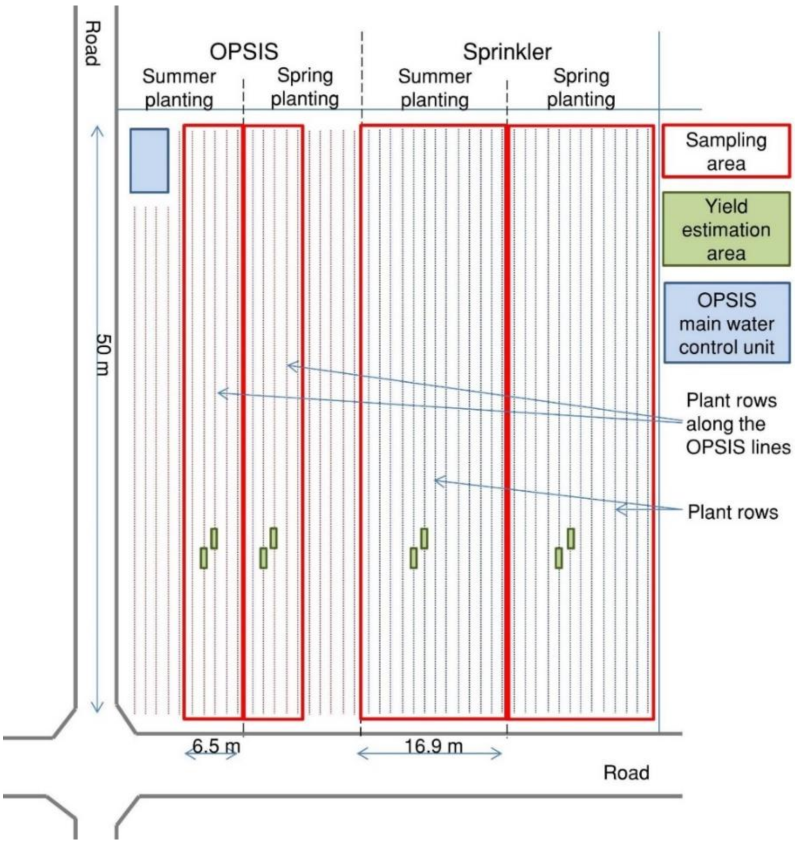

Figure 3.1. Field layout of experimental field (Teruya, Itoman) used to compare the performance of optimized subsurface irrigation system (OPSIS) and conventional sprinkler irrigation in sugarcane cultivation

Table 3.1. Planting seasons and harvesting periods of sugarcane crops used to compare the performance of two irrigation methods and climatic conditions during the periods

Planting season	Crop type	Planting date	Harvesting date	Rainfall (mm)	Max. T. (^{0}C)	Min. T (^{0}C)	Cumulative SR (MJ/m^2)
Spring	Main crop	Apr. 2013	Mar. 2014	2234	15.5 – 34.8	10.3 – 28.9	5460
	1st ratoon crop		Jan. 2015	3599	14.9 – 33.9	9.8 – 28.8	4595
	2nd ratoon crop		Jan. 2016	2303	12.5 – 33.8	6.1 – 28.8	5499
Summer	Main crop	Oct. 2013	Jan. 2015	4529	14.9 – 33.9	9.8 – 28.8	6604

Rainfall – Total rainfall during the cropping period; Max.T – Range of maximum temperature during the cropping period; Min.T – Range of minimum temperature during cropping period; Cumulative SR – Cumulative solar radiation during the cropping period

In the OPSIS treatments, ten split application of urea fertilizer was used at the rate of 350 kg/ha during the first three months of the crop. In the sprinkler irrigation treatment, the same amount of fertilizer was added as two splits after one and two months after planting, following the regular fertilizer application practice in Okinawa.

3.2.2. Irrigation system installation

For the OPSIS treatments, two plots of 6.5 m × 50 m were prepared by installing five OPSIS lines at 1.3 m spacing. Before planting, the main water control system was established (Gunarathna et al., 2017). A concrete water tank stored water, and 100 mm PVC pipes were used to make a water supply column, water distribution column, and fertilizer tank. The water control mechanism of the water supply column used a 50mm PVC pipe (inner pipe) and a 6.5 mm flexible pipe (Gunarathna et al., 2017). An automatic fertilizer tank (Gunarathna et al., 2017) supplied fertilizer to the irrigation system (Gunarathna et al., 2017). The water distribution column, which feeds five irrigation supply lines (Gunarathna et al., 2017) was set vertically at the head end of the field. The irrigation supply lines were made of 50-mm flexible perforated pipe, which was simultaneously laid together with 45-cm-wide PVC sheets (seepage barrier) using the newly developed OPSIS system laying attachment (Gunarathna et al., 2017). The irrigation lines were laid 45 cm below the soil surface. The seepage barrier was laid below the supply line forming an open trapezoidal cross-section (Gunarathna et al., 2017). The height, top width, and bottom width of the trapezoid were 15, 30, and 12 cm, respectively. In OPSIS treatments, automatic irrigation was practiced during the crop growing period and stopped in October until harvesting the crop.

For the sprinkler irrigation treatments, two plots of 16.9 m × 50 m were prepared by installing commercially available impact-type sprinklers. Irrigation was practiced on a fixed-interval irrigation schedule similar to the common practice in Okinawa.

3.2.3. Plant growth and yield sampling

Plant height and cane diameter of the summer-planted main crop and the first ratoon crop of the spring-plant were measured at monthly intervals from April 2014 to January 2015 by non-destructive sampling. The distance from the soil surface to the +1 dewlap (plant height; (de Sousa et al., 2015)) and the diameter of the middle internode of randomly selected primary shoots of five plants in the central three rows of each plot were measured.

Linear mixed-effects analysis was performed using the lme4 package (Bates et al., 2015) of R statistical software (R Core Team, 2016) to compare the effect of irrigation method on height and diameter. In the linear mixed-effect analysis, irrigation method was used as the fixed effect, and crop type (main crop or ratoon) was used as the random effect. The interaction was ignored. Residual plots were visually inspected to check the normality of errors. Likelihood ratio tests of full models (with the effect of irrigation) and null models (without the effect of irrigation) were used to test for significant differences between means.

During the harvesting of the spring- and summer-planted main crops and two ratoon crops, a 5.2 m^2 area was randomly selected in each plot to measure yield. Fresh cane weight was measured on a top-loading balance, average cane diameter of the harvest with a vernier caliper, and average millable cane length of the harvest with a measuring tape. The Brix value of the cane juice extracted from the middle internode (estimate of sugar content) was measured with a hand-held refractometer, and the values were corrected to 20 °C. The number of millable stalks was also counted as part of the yield survey. The linear model analysis was performed using R statistical software to compare the effect of irrigation method and planting season/crop type on measured yield parameters except for the number of millable stalks. Linear models for each measured parameter were set as a function of irrigation method and planting season/crop type. The interaction between irrigation method and crop type/planting season was ignored. Poisson regression analysis using the MASS package (Venables and Ripley, 2002) of R statistical software was used to compare the effect of irrigation method and planting season/crop type on the number of millable stalks. Mean separation was performed using the least significant difference (LSD) comparison of the agricolae package (Mendiburu, 2016) of R.

3.2.4. Measurement of irrigation water use

Irrigation water use in the first and second ratoon crops under sprinkler irrigation and OPSIS were surveyed during the growing periods. Irrigation of the first ratoon crop was started in April 2014 and continued until October 2014. Irrigation of the second ratoon crop was started on February 2015 and continued until October 2015. The amount of irrigation consumed in the OPSIS treatment was measured using water level recorders attached to the main water tank. The water level was recorded at 1-h intervals and converted into daily irrigation amount. The amount of irrigation water used in the sprinkler irrigation treatment was measured during each irrigation event and recorded.

3.2.5. Water use efficiency

Daily rainfall was measured with a recording rain gauge installed at the site. Effective rainfall (a portion of rainfall which can be effectively used by the plants) was calculated using the procedure explained by Brouwer and Heibloem (Brouwer and Heibloem, 1986). Total and irrigation water use efficiencies were calculated using Eqs. 1 and 2:

$$Water\,use\,efficiency\,(WUE) = \frac{Cane\,yield\,(t/ha)}{Total\,water\,applied\,(cm)} \tag{3.1}$$

$$Irrigation\,water\,use\,efficiency\,(IWUE) = \frac{Cane\,yield\,(t/ha)}{Total\,irrigation\,water\,applied\,(cm)} \tag{3.2}$$

3.3. Results and Discussion

3.3.1. Plant height during crop growth

Figure 3.2 shows how irrigation method affected the average plant height of the main summer-planted crop and the first ratoon crop of the spring-planted crop. In both crops, plant height shows the usual sigmoidal growth pattern under both irrigation methods. Linear mixed-effects analysis revealed that irrigation method significantly affected plant height ($\chi^2 = 44.36$, $P < 0.001$), with OPSIS increasing the plant height by 34.0 ± 3.4 cm which was about 12% increase compared to sprinkler irrigation.

3.3.2. Cane diameter during crop growth

Figure 3.3 shows how irrigation method affected the average cane diameter of the main summer-planted crop and the first ratoon crop of the spring-planted crop throughout crop development. Linear mixed-effects analysis revealed that irrigation method did not have a significant effect on cane diameter ($\chi^2 = 0.10$, $P = 0.75$).

3.3.3. Fresh cane yield

The OPSIS-irrigated crops all had higher fresh cane yield than the sprinkler-irrigated crops (Figure 3.4): by 9% in the spring-planted main crop, 27% in the summer-planted main crop, 44% in the first ratoon crop, and 20% in the second ratoon crop. The linear model analysis revealed that irrigation method and crop type significantly affected the fresh cane yield ($F(2, 5) = 20.3$, $P = 0.004$). OPSIS produced a significantly higher yield than sprinkler irrigation (by 23.0 ± 4.7 t/ha, $P = 0.005$). Both main crops recorded higher yields (by 8.6 ± 2.1 t/ha, $P = 0.009$) than the ratoon crops.

3.3.4. Millable cane length

Figure 3.5 shows how irrigation method affected average millable cane length in the spring-planted crop, summer-planted crop, and the first and second ratoon crops of the spring-planted sugarcane. The OPSIS-irrigated crops all had higher average millable cane length than the sprinkler-irrigated crops (Fig. 12): by 13% in the spring crop, 14% in the summer crop, 23% in the first ratoon crop, and 2% in the second ratoon crop. The linear model analysis revealed that OPSIS significantly increased the average cane length of the harvest (by 29.8 ± 11.1 cm, $P = 0.04$) relative to sprinkler irrigation.

3.3.5. Cane diameter at maturity

The cane diameter of the middle internode (Figure 3.6) was not significantly affected by irrigation type ($F(2, 5) = 2.2$, $P = 0.21$).

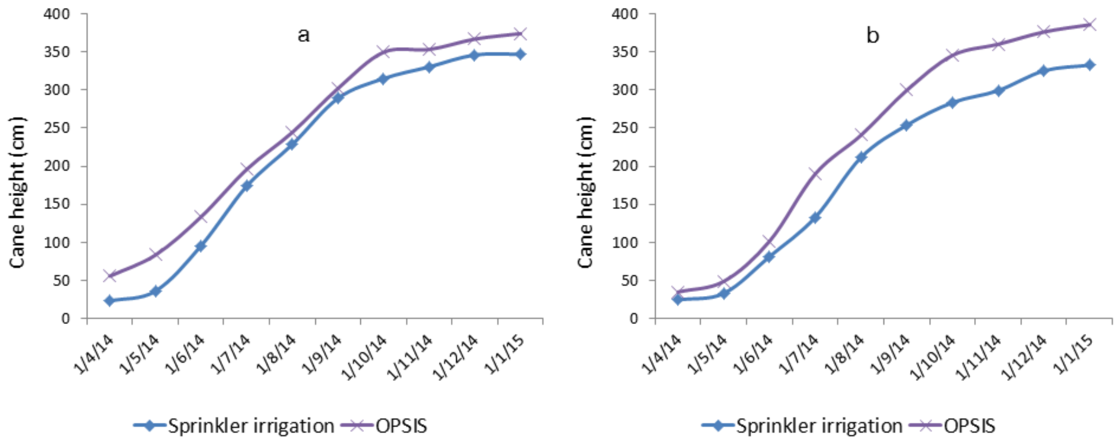

Figure 3.2. Average plant height of sugarcane cultivar Ni21 as affected by irrigation method in (a) the summer-planted main crop and (b) the first ratoon crop of spring-planted sugarcane

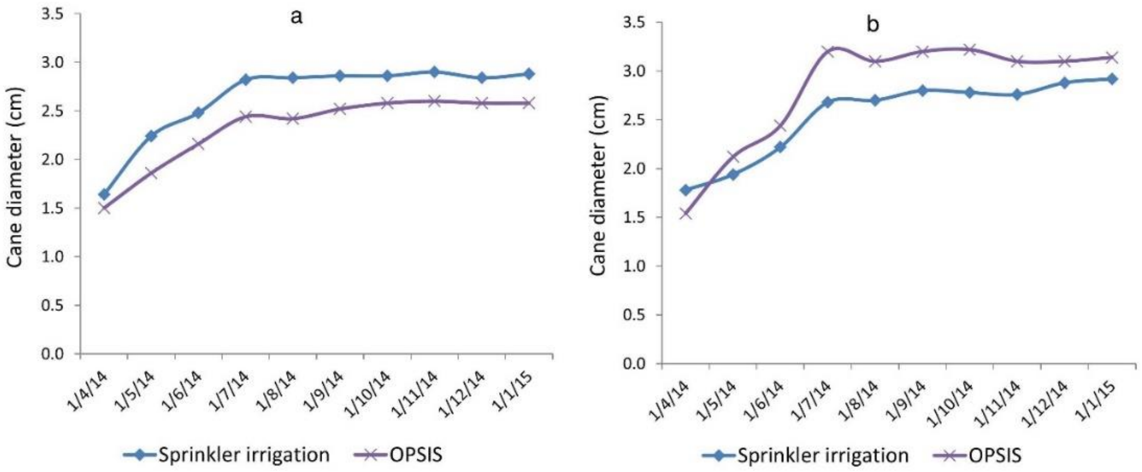

Figure 3.3. Average cane diameter of sugarcane cultivar Ni21 as affected by irrigation method in (a) the summer-planted main crop and (b) the first ratoon crop of spring-planted sugarcane

3.3.7. Brix value

Figure 3.8 shows how irrigation method affected the Brix value of juice extracted from the middle internode in the four crops. The linear model analysis revealed that irrigation method and crop type did not affect the Brix value of cane juice ($F(2, 5) = 0.62$, $P = 0.57$).

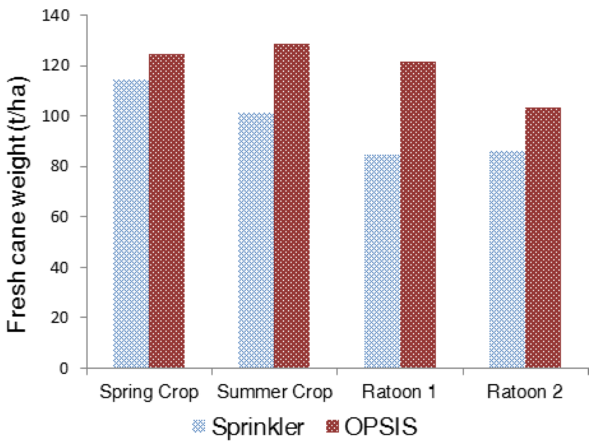

Figure 3.4. Fresh cane yield of sugarcane cultivar Ni21 as affected by irrigation method

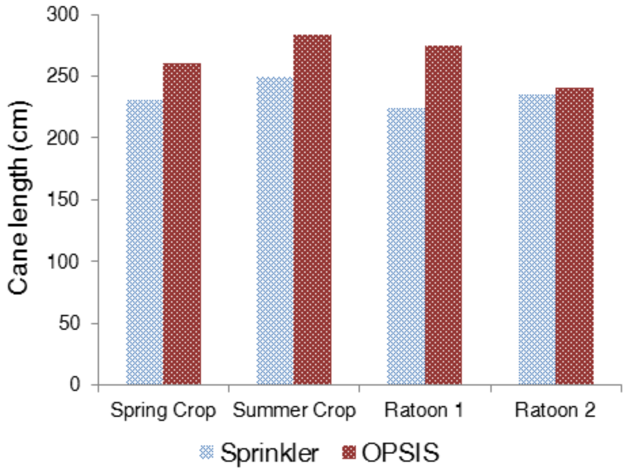

Figure 3.5. Average millable cane length of sugarcane cultivar Ni21 as affected by irrigation method

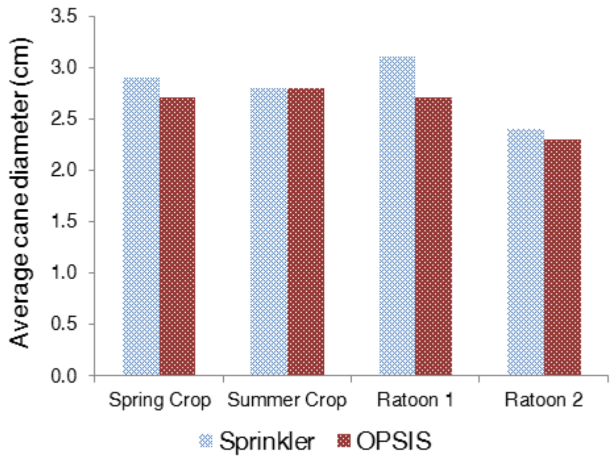

Figure 3.6. Average cane diameter of sugarcane cultivar Ni21 as affected by irrigation method

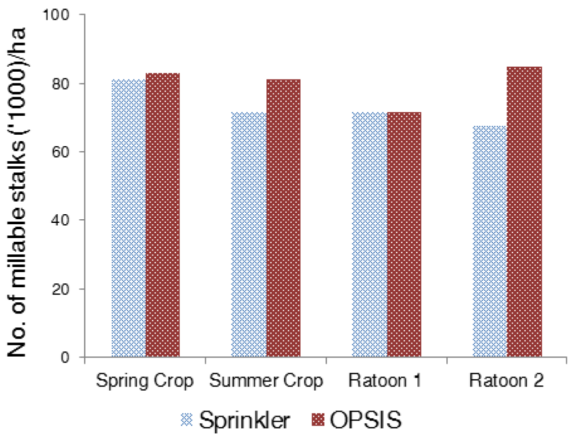

Figure 3.7. Number of millable stalks of sugarcane cultivar Ni21 as affected by irrigation method

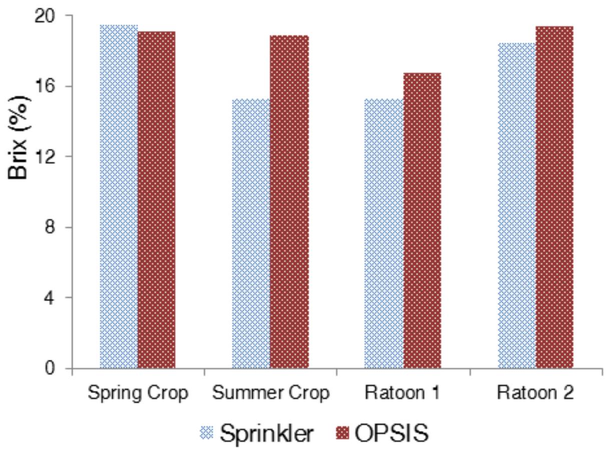

Figure 3.8. Average Brix value of cane juice of sugarcane cultivar Ni21 as affected by irrigation method

Our results confirm that the sugarcane yield was higher with OPSIS than with conventional sprinkler irrigation, and the higher yield was achieved by increased millable cane length and number of millable canes.

In previous studies, optimum soil moisture (Ramesh and Mahadevaswamy, 2000) and nutrient supply (Chen et al., 2012) have been found to increase the number of millable stalks, a significant contributor to the economic yield, because water and nutrient stresses reduce tiller production and increase tiller mortality. Because water availability directly influences cell turgor (Levitt, 1980) and thus cell growth and development, increased plant height and canopy development of sugarcane have been reported when moisture and nutrient stresses are removed (Ramesh and Mahadevaswamy, 2000). Optimum soil moisture (Juan et al., 2016) and nutrient availability (McCormick et al., 2006) have also been shown to increase the photosynthetic rate in sugarcane.

Juan et al. (2016) examined mean net photosynthetic rate in the sugarcane cultivar Liucheng 05-136 under six irrigation methods and found that photosynthetic rate was highest in the subsurface drip irrigation treatment, which was 58% higher than with no irrigation, 24% higher than with pipe irrigation, 13% higher than with sprinkler irrigation, 10% higher than with micro-sprinkler irrigation, and 3% higher than with surface drip irrigation. They concluded that the irrigation method significantly affects the photosynthetic rate of sugarcane plants. Further, using Path analysis, they reported soil water content, air temperature, and soil fertility as the main environmental factors influencing sugarcane net photosynthetic rate, with some differences in these among irrigation methods. Fertigation improves the utilization of fertilizer and therefore can boost plant growth, increase the number of effective tillers, promote stalk elongation and diameter enlargement, and ultimately increase the millable cane yield (Chen et al., 2012). Similarly, Sivanappan (2014) reported that soil fertility limitations, poor water management, and unbalanced nutrient management are the significant barriers to achieving maximum potential sugarcane yields. Proper irrigation and nutrient management are, therefore, essential to achieving sugarcane yields close to the potential. The higher yields in furrow irrigation than in rainfed conditions (Basnayake et al., 2012; Silva and Costa, 2004), in surface and subsurface drip irrigation than in surface irrigation (Hanafy et al., 2008; Surendran et al., 2016), and in subsurface drip irrigation than in sprinkler irrigation (Shrivastava et al., 2011) are on par with the importance of water and nutrient management in achieving higher yields near close to the potential yield.

Fertigation is an effective method of increasing sugarcane yield as it manages both water and nutrients more effectively than conventional fertilizer application. A study reported a 32% higher sugarcane yield with drip fertigation than with conventional fertilizer application (without drip irrigation), and a 23% higher yield than with drip irrigation plus conventional fertilizer application (Chen et al., 2012). Abdel Wahab (2014) reported higher growth and yield performances of sugarcane with fertigation than with conventional fertilizer application, in both cases using a gated pipe surface irrigation system. Similarly, in the current study, OPSIS have higher growth and yield of sugarcane than sprinkler irrigation. Since all physiological processes depend on water and nutrient availability, and the adverse effects of water and nutrient stress on physiological processes (Inman-Bamber, 2004) and canopy development (Smit et al., 2004) are well understood, it is clear that the higher growth and yield of sugarcane from OPSIS derives from the better water and nutrient management afforded by it.

3.3.8 Irrigation water use

During April 2014 to January 2015, the research field received 3342 mm of rainfall (higher than the average of 2200 mm for the area), of which an estimated 2474 mm was effective rainfall. Therefore, both irrigation methods consumed low amounts of irrigation water during the growing period of the first ratoon crop. However, the results showed that OPSIS (82 mm) consumed only 46% of the water consumed by sprinkler irrigation (178 mm). During the second ratoon crop, the field received 2239 mm of rainfall, of which an estimated 1545 mm was effective. During this period, OPSIS (323 mm) used 79% of the water used by sprinkler irrigation (409 mm). In the sprinkler irrigation, although antecedent rainfall was taken into consideration, irrigation timing followed the irrigation schedule decided in the region. Therefore, more irrigation water was used than needed. On the other hand, OPSIS does not use much water when soil moisture is near saturation. Therefore, OPSIS used less water than sprinkler irrigation, and the difference was significant when rainfall was above average. The difference is attributed to OPSIS having a more precise application, an absence of runoff, and minimal evaporation compared with sprinkler irrigation.

3.9. Water use efficiency

In the first ratoon crop, OPSIS recorded IWUE of 14.8 t/ha/cm, which was 3.1 times that of sprinkler irrigation (4.8 t/ha/cm). Because of the high rainfall received during this season, the total WUE was low in both methods: 0.47 t/ha/cm in OPSIS and 0.32 t/ha/cm in sprinkler irrigation. During the second ratoon crop, OPSIS recorded an IWUE of 3.2 t/ha/cm, which was 1.5 times that of sprinkler irrigation (2.1 t/ha/cm). The total WUEs of OPSIS and sprinkler irrigation were 0.55 and 0.44 t/ha/cm, respectively.

Our results confirm that OPSIS achieves higher total WUE and IWUE than sprinkler irrigation. Kumawat et al. (2016) reported 56% higher WUE with drip irrigation (5.96 t/ha/cm) than with surface irrigation (3.32 t/ha/cm), as well as minimal water losses and higher yields. Even with a yield penalty due to increased residues, the use of residue as cover significantly increased IWUE relative to bare soil by cutting evaporation losses (Olivier and Singels, 2015). Gupta and Singh (2015) reported that the ability of drip irrigation to significantly increase IWUE relative to furrow irrigation was due to both lower water use and higher yields (attributed to more millable stems and increases in both stem length and diameter). Similarly, in our study, OPSIS resulted in higher IWUE (fewer losses) and higher yields than sprinkler irrigation. It also returned a higher total WUE and higher IWUE than sprinkler irrigation, which derives from both higher crop yield and lower irrigation water consumption than in sprinkler irrigation.

Under rainfall conditions close to the average (during ratoon 2), the water savings were less than when rainfall was above average (during ratoon 1). This result suggests that there were water losses, probably due to percolation, when water was close to average. Therefore, measures should be taken to control the percolation losses. Gunarathna et al.

(2017) suggested changing the solar-radiation–triggered automatic operation mechanism to a soil-moisture–based automatic operation mechanism to minimize percolation losses.

3.4. Conclusions

This study showed that OPSIS offers advantages over sprinkler irrigation for sugarcane cultivation in Okinawa in respect of both sugarcane yield and WUE. Compared with sprinkler irrigation, OPSIS produced significantly taller plants, and thus significantly longer millable stalks, and significantly more millable stalks. Therefore, OPSIS achieved significantly higher fresh cane weight using less irrigation water than did sprinkler irrigation. OPSIS is a water-conserving irrigation technique that can irrigate sugarcane crops with minimal operational cost, energy consumption, and human intervention. Therefore, it may be a sustainable alternative for sugarcane crop irrigation in Okinawa and similar subtropical environments.

3.5. Recommendations

Further studies are needed to validate the long-term viability of OPSIS as a sustainable alternative to current irrigation methods used in sugarcane farming systems. We need to confirm that the benefits revealed in the current study hold under different climatic, soil, and management conditions and, wherever possible, identify improvements to the system.

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4.0 Sensitivity Analysis of Plant- and Cultivar-Specific Parameters of APSIM-Sugar Model

This chapter is based on Gunarathna, M.H.J.P., Sakai, K., Nakandakari, T., Momii, K., Kumari, M.K.N., 2019. Sensitivity Analysis of Plant- and Cultivar-Specific Parameters of APSIM-Sugar Model: Variation between Climates and Management Conditions. Agronomy 9, 242. https://doi.org/https://doi.org/10.3390/agronomy9050242

4.1 Introduction

The production of sugarcane is increasing in importance as both food and a source of energy. Thus, productivity needs to improve continuously. The frequent introduction of new cultivars (Lisson et al., 2005; Sexton et al., 2017) and management strategies (Gunarathna et al., 2018b, 2017; Surendran et al., 2016) 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 (Holzworth et al., 2014; Keating et al., 1999) and the Decision Support System for Agrotechnology Transfer (DSSAT)-Canegro model (Jones et al., 2003) can simulate growth and yield of sugarcane under different environmental (climatic and soil) and management (irrigation, fertilization, etc.) conditions with different cultivars (Sexton et al., 2017). Crop models have been used for decision support in sugarcane farming, including irrigation scheduling (Everingham et al., 2008; Inman-Bamber and McGlinchey, 2003), harvest scheduling (Bocca et al., 2015; Lisson et al., 2005), and fertilizer management (Gaydon et al., 2017). They are also used in projecting the influence of climate change (Singels et al., 2014; Thorburn et al., 2014; Zubair et al., 2015) and guiding varietal improvement (Basnayake et al., 2012). However, most crop models are limited to old cultivars, so studies of varietal differences are limited (Inman-Bamber et al., 2016). 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 (Sexton et al., 2017). 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 critical parameters that need to be estimated by varietal calibration.

SA techniques can be broadly categorized as local or global (Saltelli et al., 2008); local SA considers a single parameter at a time, and global SA considers the combined effect of multiple parameters. Saltelli et al. (2010) 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. (2017) 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 (O'Hagan, 2006) used in place of computationally expensive models. An emulator with a high enough accuracy can replace an actual simulator to perform SA (Uusitalo et al., 2015). In this approach, initially the simulator runs for relatively few simulations to build the emulator, then the emulator is used for the SA.

4.1.1 Objectives of the Study

Objectives of the study are,

1. To assess 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.
2. To identify the important candidates for the parameterization and calibration of APSIM-Sugar in different environments and management conditions.

3. To assess the effect of radiation use efficiency (RUE) and transpiration efficiency (TE) on the parameterization and calibration of APSIM-Sugar.

4. To assess the relationship between the variations in influence and climate.

4.2 Materials and Methods

4.2.1. 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) (Gima and Yoshitake, 2016). In Sri Lanka, sugar is an essential subsector in the economy, with great potential for employment and income generation and the development of the 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) (Buysse, 2002). In Okinawa, the 30-year average monthly maximum and minimum temperatures both differ by about 15 °C between summer and winter (Figure 4.1a). In Sri Lanka, they differ by only 2 to 3 °C (Figure 4.1b). Solar radiation shows high seasonal variation in Okinawa (15 MJ/m^2/day), but less (6 MJ/m^2/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 4.1).

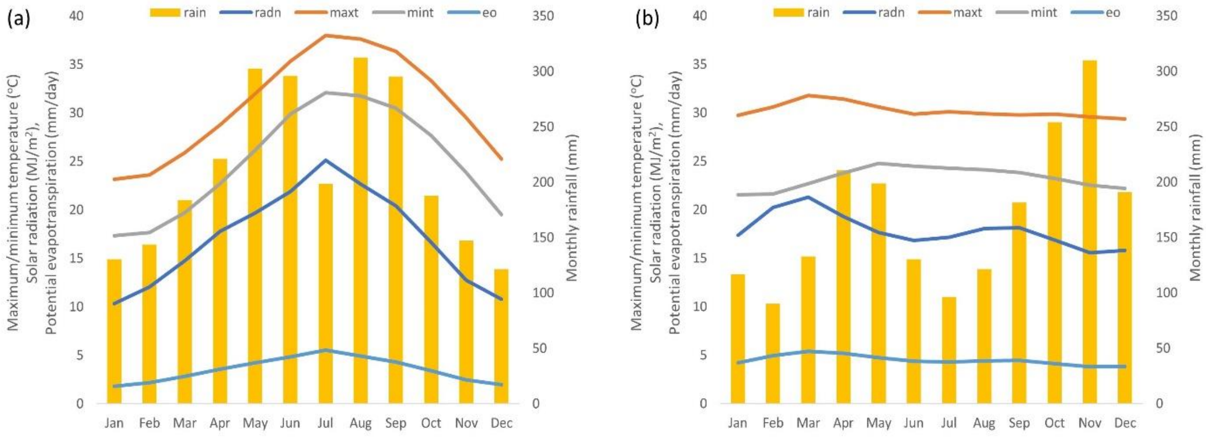

Figure 4.1. Average monthly climate data of (a) Itoman, Okinawa, Japan (1980-2010) and (b) Sevanagala, Monaragala, Sri Lanka (1980-2010); rain, mean monthly rainfall (mm); radn, mean daily solar radiation (MJ/m^2); maxt, mean daily maximum temperature (^{0}C); mint, mean daily minimum temperature (^{0}C); eo, Potential evapotranspiration (mm/day)

4.2.2. 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 (Holzworth et al., 2014; Keating et al., 2003). 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 (Keating et al., 1999). 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) (Keating et al., 1999; Sexton et al., 2017). This process is controlled by environmental (soil and climate), plant or ratoon, and cultivar-specific parameters (Dias et al., 2019; Keating et al., 2000, 1999).

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 (Gunarathna et al. (2019b), and other data were gathered from a report by the Soil Science

Society of Sri Lanka (Dassanayake et al., 2010). Soil data for Okinawa were collected through comprehensive soil analysis. Meteorological data for Sri Lanka were extracted from the AgMERRA global gridded climate dataset (Ruane et al., 2015) 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 4.1 shows the variation of climatic variables used for these simulations. Table 4.1 summarizes the soil and management conditions of the two locations.

Table 4.1. Soil and management conditions of selected locations used for the simulations

Location	Itoman, Okinawa, Japan	Sevanagala, Monaragala, Sri Lanka
	26° 7' 58"N 127° 40' 52"E	6° 22' 13"N 80° 54' 47"E
Soil	Shimajiri Mahji	Solodized Solonetz
	Depth: 110 cm	Depth: 100 cm
	PAWC: 68.4 mm	PAWC: 91.6 mm
	Average bulk density 1.11g/cm^3	Average bulk density 1.37g/cm^3
Planting	April 01 (Spring planting)	April 01 (Yala season planting)
Crop duration	315 days	360 days
Stalk density	7 stalks/m^2	8 stalks/m^2
Fertilizer	190 kg/ha as NH_4-N	200 kg/ha as Urea
Fertilizer application time	31 and 62 days after planting	45 and 90 days after planting
Irrigation	Automatic irrigation	
	The fraction of ASW below which irrigation is applied = 0.5	
	The efficiency of the irrigation = 0.5	

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

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

GEM-SA is open-source software used to build software emulators from a set of inputs and outputs to perform predictions, uncertainty analysis, and SA using far fewer code runs than Monte Carlo–based methods (Kennedy and Petropoulos, 2017). It uses Bayesian analysis of computer code outputs (Kennedy and O'Hagan, 2001). The underlying mathematical procedures used in GEM-SA and analytical procedures used to conduct SA with GEM-SA are described in full by Kennedy and O'Hagan (2001), Kennedy et al. (2006) and Kennedy and Petropoulos (2017). 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 (Oakley and O'Hagan, 2004). Gunarathna et al. (2019a) reported the accuracy of emulators developed by GEM-SA for subtropical environments. Sexton et al. (2017) 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. (2018a) 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 4.2). 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 4.2 shows an overview of the procedure we used for this study.

Table 4.2. 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	mm^2	500 – 2000
	Leaf_size_no = 14	LS2	mm^2	25000 – 70000
	Leaf_size_no = 20	LS3	mm^2	25000 – 70000
cane_fraction *(Fraction of accumulated biomass partitioned to cane)*		CF	gg^{-1}	0.65 - 0.80
sucrose_fraction_stalk *(Fraction of accumulated biomass partitioned to sucrose)*	Stress factor = 1	SF	gg^{-1}	0.50 – 0.70
sucrose_delay *(Sucrose accumulation delay)*		SD	gm^{-2}	0 – 600
min_sstem_sucrose *(Minimum stem biomass before partitioning to sucrose commences)*		MSS	gm^{-2}	450 – 1500
min_sstem_sucrose_redn *(reduction to minimum stem sucrose under stress)*		MSSR	gm^{-2}	0 – 20
tt_emerg_to_begcane *(Accumulated thermal time from emergence to beginning of cane)*		EB	˚C day	1200-1900
tt_begcane_to_flowering *(Accumulated thermal time from beginning of cane to flowering)*		BF	˚C day	5500 – 6500

tt_flowering_to_crop_end *(Accumulated thermal time from flowering to end of the crop)*		FC	°C day	1750 – 2250
green_leaf_no *(Maximum number of fully expanded green leaves)*		GLN	No.	9 – 14
tillerf_leaf_size *(Tillering factors according to the leaf numbers)*	Tiller_leaf_size_no = 1	TLS1	$mm^2\ mm^{-2}$	1 – 6
	Tiller_leaf_size_no = 4	TLS2	$mm^2\ mm^{-2}$	1 – 6
	Tiller_leaf_size_no = 10	TLS3	$mm^2\ mm^{-2}$	1 – 6
	Tiller_leaf_size_no = 16	TLS4	$mm^2\ mm^{-2}$	1 – 6
	Tiller_leaf_size_no = 26	TLS5	$mm^2\ mm^{-2}$	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

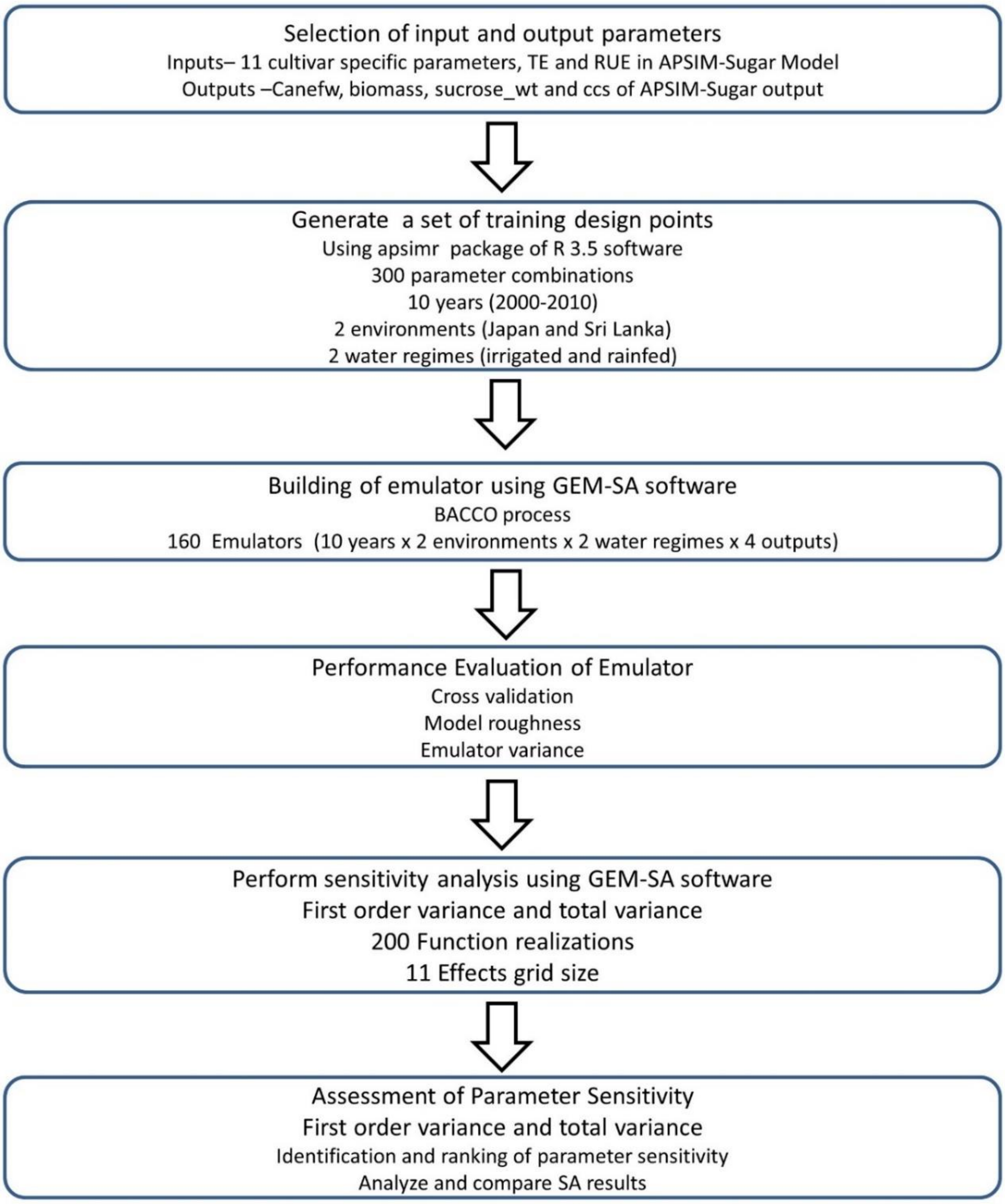

Figure 4.2. Flowchart of the analysis procedure used for the study

4.2.4. 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 four yield outputs to 13 parameters (11 cultivar-specific parameters, RUE, and TE; Table 4.2) under rainfed and irrigated conditions in two distinct environments (Figure 4.2). Initially, 300 test points (of every parameter and outputs) evenly distributed between lower and upper bounds (Table 4.2) and related outputs of APSIM were generated by the apsimr package (Stanfill, 2015) of R software (R Core Team, 2018). 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 (Kennedy et al., 2006) to develop 160 emulators (10 years × 4 outputs × 2 environments × 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:

$$S_i = \frac{Var\{E(f(X|x_i)\}}{Var\{f(X)\}} \tag{4.1}$$

Where, *Var{f(X)}* is the total variance in the output given variations in all parameters; *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 (Sexton et al., 2017). 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 (Oakley and Hagan, 2004). The total sensitivity index (ST_i) is defined as:

$$ST_i = 1 - \frac{Var\{E(f(X|x_{-i})\}}{Var\{f(X)\}} \tag{4.2}$$

Where, *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 (2010) suggested using ST_i when sensitivity analysis aims to set non-influential parameters to default values and to remove 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 know the exact values. Therefore, the error values are readily available (Petropoulos et al., 2015). 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 (Kennedy and Petropoulos, 2017), and the sigma squared (σ^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.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y})^2}{n}} \tag{4.3}$$

$$RMSSE = \sqrt{\frac{\sum_{i=1}^{n}((y_i - \hat{y})/s_i)^2}{n}} \tag{4.4}$$

Where, y_i is the true output for the ith training run, $\hat{y}$ is the corresponding emulator approximation, s_i is the standard deviation calculated with the ith training point removed, and n is the number of runs (Kennedy and Petropoulos, 2017).

4.3. Results and Discussion

4.3.1. Emulator accuracy

A series of internally calculated statistical measures (σ^2, RMSE, and RMSSE) of GEM-SA were used to quantify the uncertainty of the sensitivity analysis due to emulation of model simulation (Kennedy and Petropoulos, 2017). We used σ^2 (variance of the emulator after standardization of output) to evaluate the linearity of the GEM-SA emulators, as σ^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. (2009) reported that their emulators showed linearity or moderate nonlinearity at σ^2 values between 0.13 and 1.6. We got σ^2 values of 0.15 to 1.43 for Okinawa and 0.10 to 0.59 for Sri Lanka (Figure 4.3), 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 4.3). These values are lower than previously reported values of emulators assessed as satisfactory (Kennedy and Petropoulos, 2017; Lee et al., 2011; Petropoulos et al., 2009).

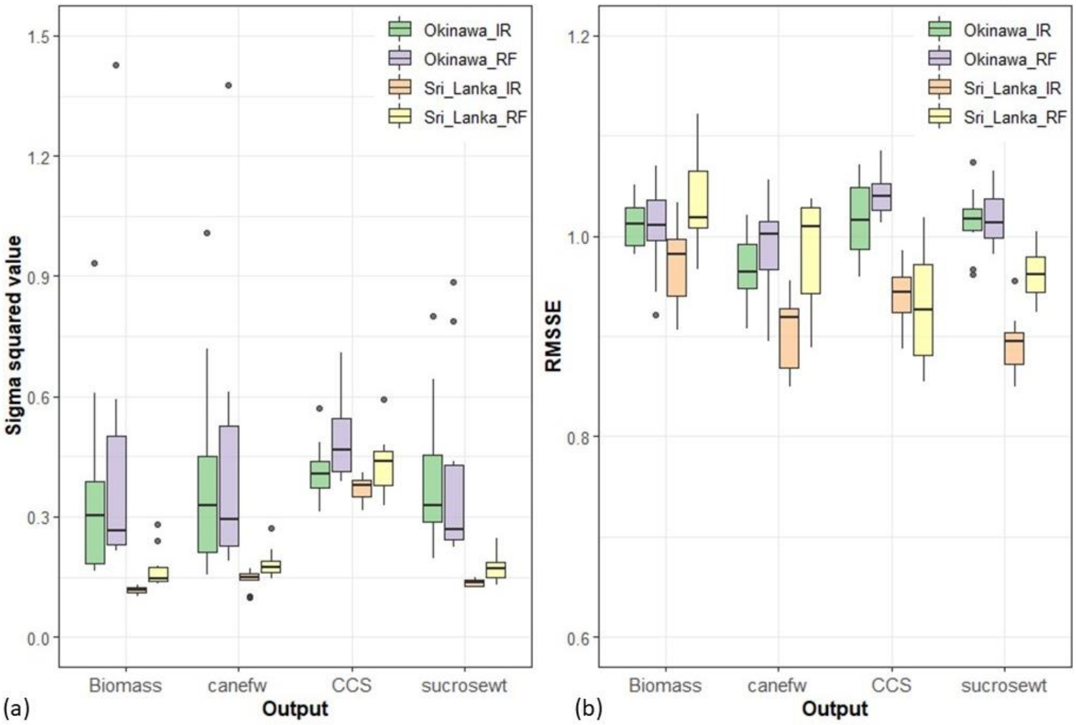

Figure 4.3. (a) Sigma squared value, (b) Cross validated Cross-validation root mean squared standardized error of results of selected outputs under two climatic conditions (Okinawa and Sri Lanka). IR, Irrigated; RF, rainfed.

4.3.2. The 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 4.4–4.7) and among years. There were no significant differences between the main and total effect indices, and the main effect index was able to explain a significant 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 higher in Okinawa than in Sri Lanka as a result of the 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 4.3). Significant contributions (over 1%) is highlighted (bold) in Table 4.3.

RUE of growth stage 4 (from the beginning of cane growth to flowering; RUE4) was the most influential on all the four tested model outputs despite locations and management (Table 4.3 and Figures 4.4 to 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 the 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 (Sexton and Everingham, 2014). This was more pronounced under Sri Lanka growing conditions, probably because of the higher water-holding capacity of the Sri Lankan soil (Table 4.1). 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. (2017) 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 4.3). 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.

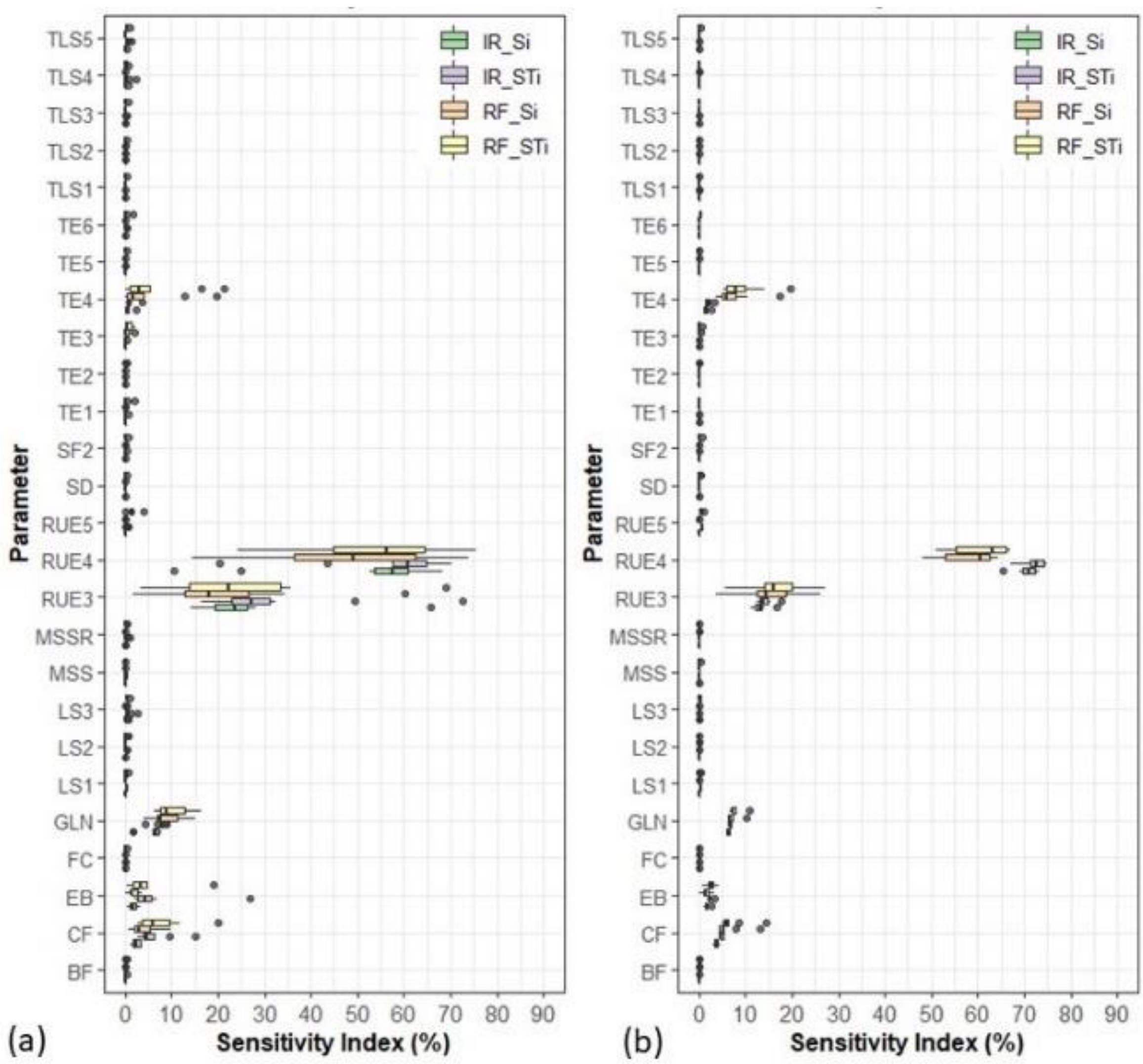

Figure 4.4. Sensitivity of APSIM-Sugar biomass (g/m^2) to parameters in (a) Okinawa and (b) Sri Lanka; Si, main effect; STi, total effect; IR, irrigated; RF, rainfed; $TLS_{1\text{-}5}$, tiller leaf size; $TE_{1\text{-}6}$, transpiration efficiency; SF2, sucrose fraction under stress; SD, sucrose delay; $RUE_{3\text{-}5}$, radiation use efficiency; MSS, minimum structural stem sucrose; MSSR, MSS reduction; $LS_{1\text{-}3}$, 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.

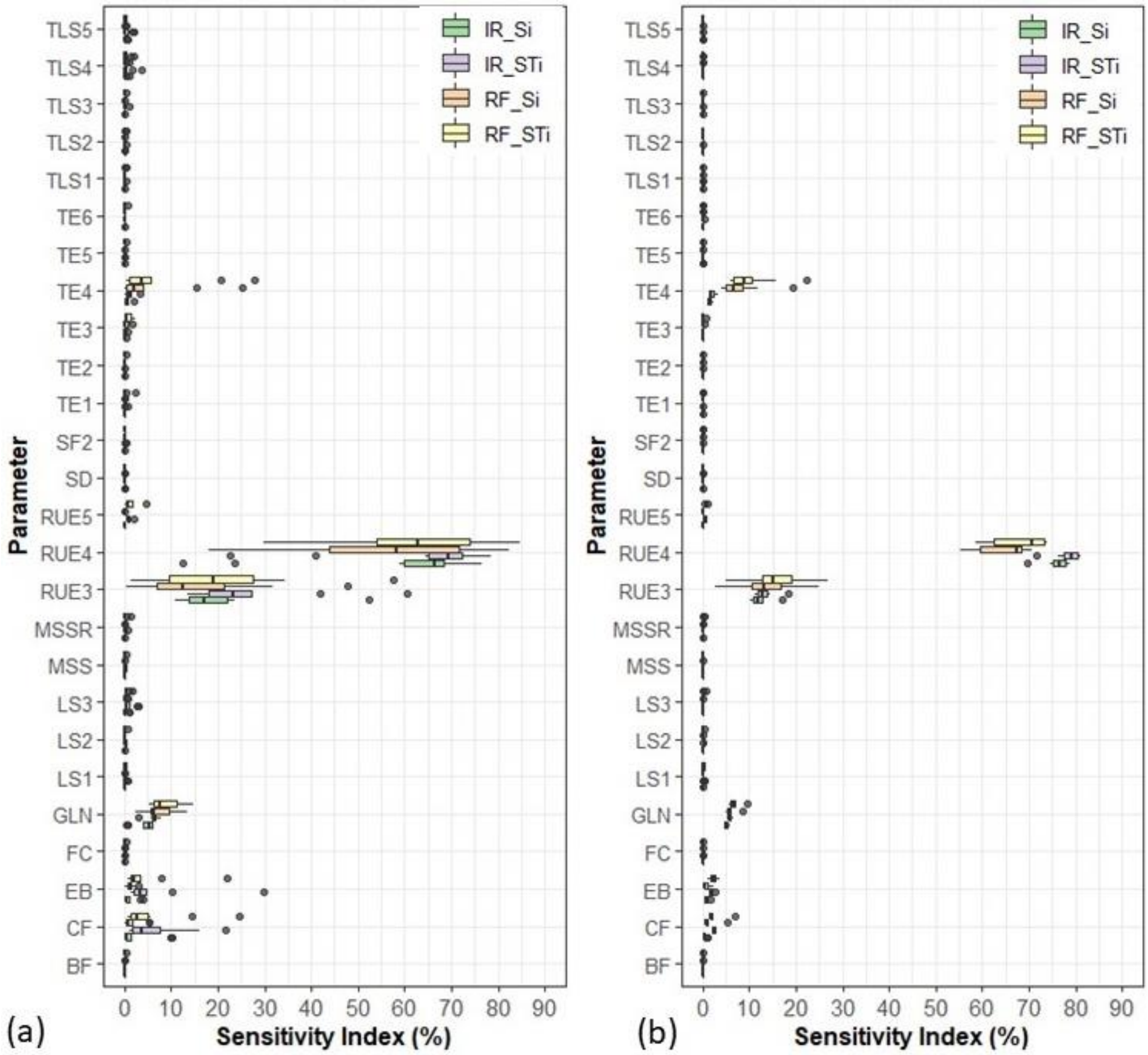

Figure 4.5. The sensitivity of APSIM-Sugar fresh cane yield (t/ha) to parameters in (a) Okinawa and (b) Sri Lanka. Si, main effect; STi, total effect; IR, irrigated; RF, rainfed; TLS_{1-5}, tiller leaf size; TE_{1-6}, transpiration efficiency; SF2, sucrose fraction under stress; SD, sucrose delay; RUE_{3-5}, radiation use efficiency; MSS, minimum structural stem sucrose; MSSR, MSS reduction; LS_{1-3}, 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.

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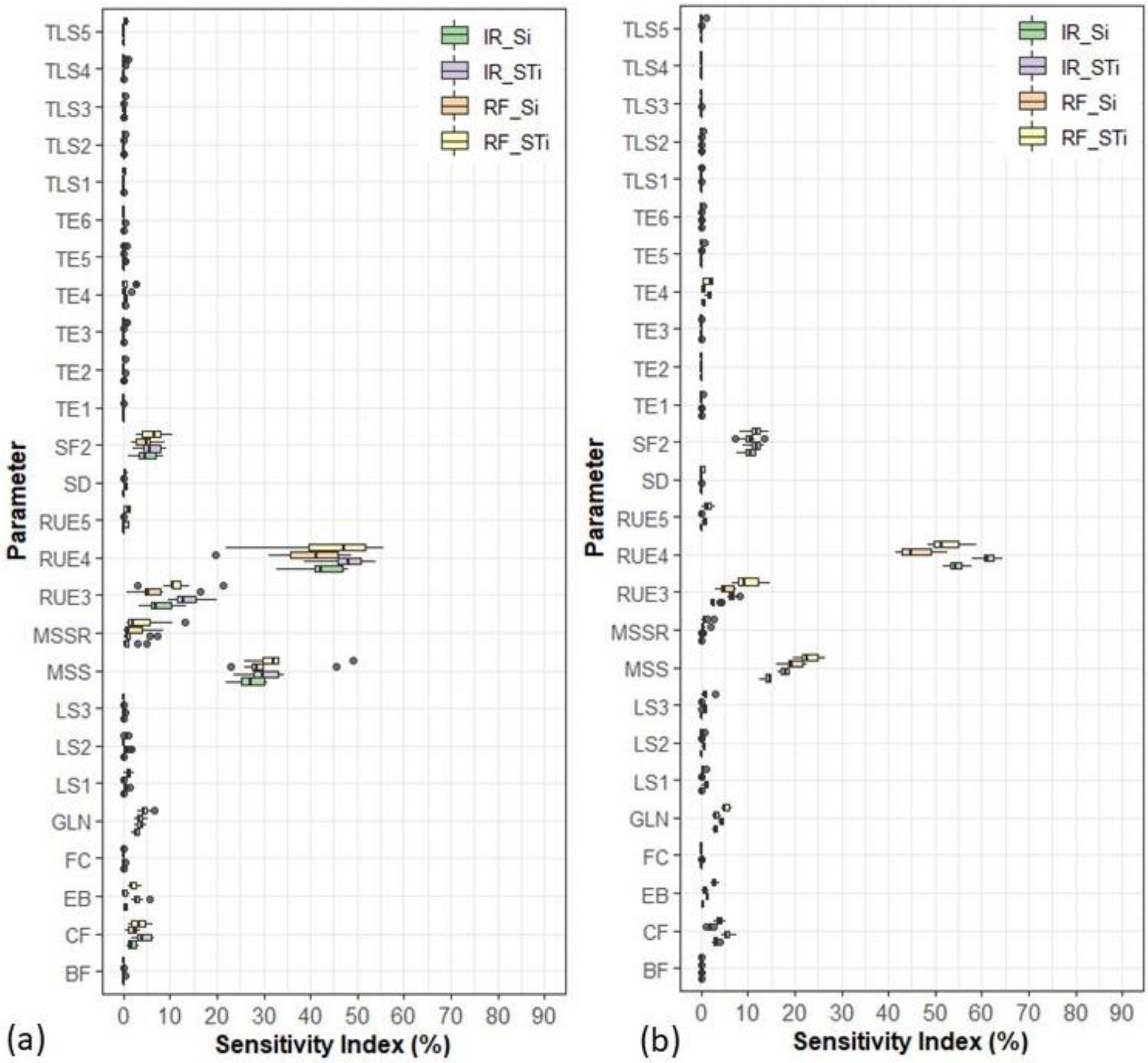

Figure 4.6. The sensitivity of APSIM-Sugar commercial cane sugar (%) to parameters in (a) Okinawa and (b) Sri Lanka. Si, main effect; STi, total effect; IR, irrigated; RF, rainfed; TLS_{1-5}, tiller leaf size; TE_{1-6}, transpiration efficiency; SF2, sucrose fraction under stress; SD, sucrose delay; RUE_{3-5}, radiation use efficiency; MSS, minimum structural stem sucrose; MSSR, MSS reduction; LS_{1-3}, 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.

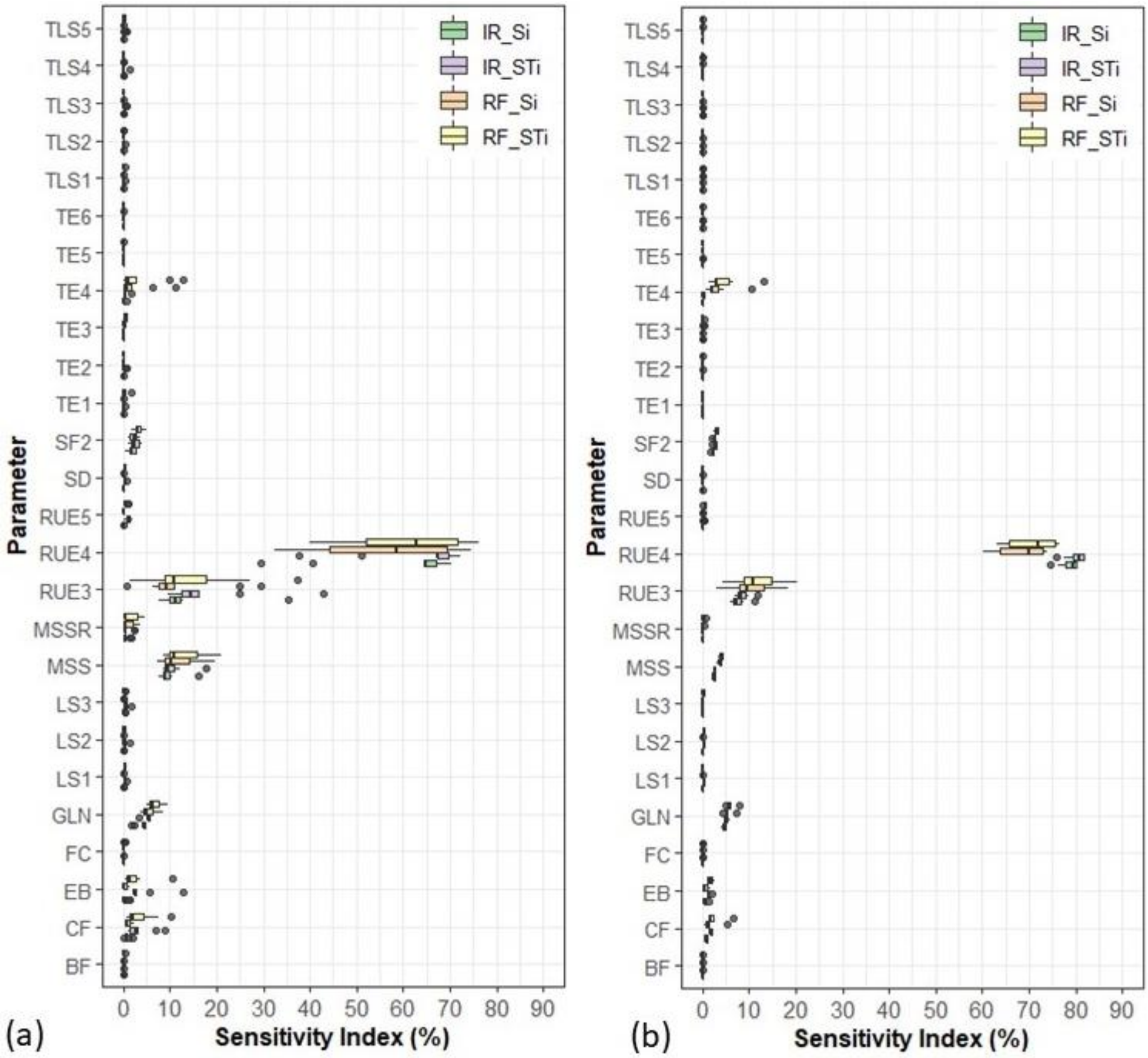

Figure 4.7. The sensitivity of APSIM-Sugar sucrose yield (g/m^2) to parameters in (a) Okinawa and (b) Sri Lanka. Si, main effect; STi, total effect; IR, irrigated; RF, rainfed; TLS_{1-5}, tiller leaf size; TE_{1-6}, transpiration efficiency; SF2, sucrose fraction under stress; SD, sucrose delay; RUE_{3-5}, radiation use efficiency; MSS, minimum structural stem sucrose; MSSR, MSS reduction; LS_{1-3}, 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.

Table 4.3. Most influential Parameters in the simulation of biomass, canefw, ccs, and sucrose_wt in APSIM-Sugar under different environments (bold indicates parameters that contributed >1% of variation).

	Biomass				Cane fresh weight				CCS				Sucrose weight			
	RF		IR		RF		IR		RF		IR		RF		IR	
Parameter	Si	Rank	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	**58.5**	1	**64.6**	1
RUE3	**18.0**	2	**23.6**	2	**12.6**	2	**17.2**	2	**5.4**	3	**7.0**	3	**9.2**	3	**11.2**	2
GLN	**7.7**	3	**6.7**	3	**6.2**	3	**5.3**	3	**3.4**	5	**2.7**	5	**4.9**	4	**4.3**	4
CF	**3.1**	4	**2.5**	4	0.6	6	0.5	6	**2.3**	6	**1.7**	6	0.7	6	0.6	6
TE4	**1.7**	5	0.5	6	**2.0**	4	0.5	5	0.1	10	0.0	11	0.7	7	0.1	9
EB	**1.4**	6	**1.8**	5	**1.0**	5	0.5	4	0.2	8	0.2	8	0.2	9	0.2	8
MSS	0.0	22	0.0	18	0.0	22	0.0	16	**28.5**	2	**27.3**	2	**10.1**	2	**8.8**	3
MSSR	0.0	17	0.0	25	0.0	21	0.0	25	**1.2**	7	0.5	7	0.3	8	0.3	7
SF	0.0	14	0.0	16	0.0	16	0.0	19	**5.0**	4	**4.8**	4	**2.2**	5	**1.6**	5
	Monaragala, Sri Lanka															
RUE4	**60.5**	1	**71.1**	1	**67.5**	1	**76.4**	1	**44.8**	1	**54.2**	1	**70.1**	1	**79.3**	1
RUE3	**14.5**	2	**13.0**	2	**13.1**	2	**11.7**	2	**5.1**	4	**2.5**	6	**9.4**	2	**7.4**	2
GLN	**6.7**	3	**6.2**	3	**5.7**	4	**5.0**	3	**3.2**	5	**2.9**	5	**5.2**	3	**4.5**	3
CF	**5.3**	5	**3.7**	4	0.7	5	0.3	6	**1.9**	6	**3.0**	4	**1.0**	7	0.7	6
TE4	**6.0**	4	**1.4**	6	**6.7**	3	**1.4**	4	0.6	8	0.5	7	**2.0**	6	0.1	8
EB	**1.5**	6	**1.6**	5	0.5	6	0.7	5	0.8	7	0.3	8	0.4	8	0.4	7
MSS	0.0	18	0.0	11	0.0	23	0.0	13	**19.5**	2	**14.8**	2	**3.8**	4	**2.5**	4
MSSR	0.0	16	0.0	12	0.0	21	0.0	20	0.3	9	0.1	9	0.1	9	0.0	9
SF	0.0	23	0.0	8	0.0	26	0.0	18	**10.4**	3	**10.5**	3	**2.6**	5	**2.3**	5

Biomass, total aboveground biomass (g/m^2); Cane fresh weight (t/ha); CCS, commercial cane sugar (%); sucrose weight (g/m^2); 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.

4.3.3. Role of RUE4 on APSIM-Sugar simulations

Daily dry matter production (DDMP; g/m^2) 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/m^2) 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 4.5).

$$I = I_0 \times EXP(-k \times LAI) \quad (4.5)$$

Where,

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

During growth stage 4, DDMP had a close relationship with solar radiation in both environments (Figure 4.8), 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 high and low temperatures (Zhao et al., 2014). No nitrogen stress was reported during this period in either environment (see 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, especially in days with higher intercepted solar radiation (Figure 4.9c). During the study period, the minimum and maximum temperatures were within the optimum range (15–45 °C, Figure 4.9a) (Martiné et al., 1999), and no nitrogen deficit and only slight water stress were recorded (Figure 4.9b). There was no water stress on days with radiation of <15 MJ/m^2 (Figure 4.9d), and APSIM-Sugar operates with maximum RUE. RUE can be maximized with favorable water, nitrogen, and temperature conditions (Zhao et al., 2014), and some authors reported higher RUE values than 2 g/MJ (De Silva and De Costa, 2012; Ferreira (Jr) et al., 2015; Martin and Acreche, 2017) 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.

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 (De Silva and De Costa, 2012), so it needs to be parameterized to achieve useful simulations. Sexton et al. (2017, 2014) 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. (2017), 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. (2014) 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 appropriately calibrated.

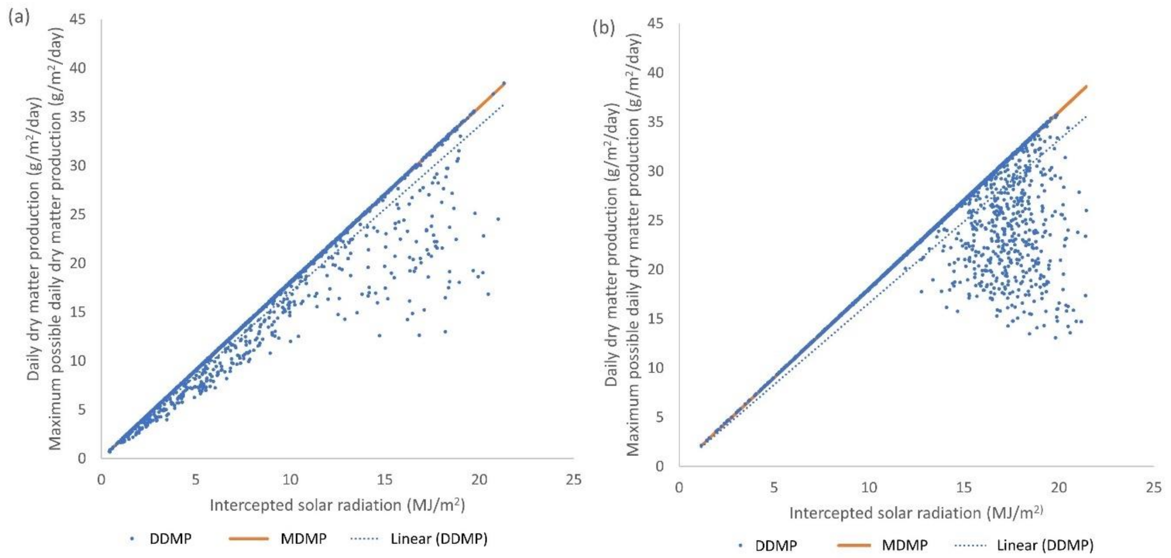

Figure 4.8. Relationship of intercepted solar radiation (MJ/m^2) during growth stage 4 with simulated daily dry matter production (g/m^2) of irrigated sugarcane and calculated maximum possible daily dry matter production (g/m^2) of sugarcane in (a) Okinawa and (b) Sri Lanka.

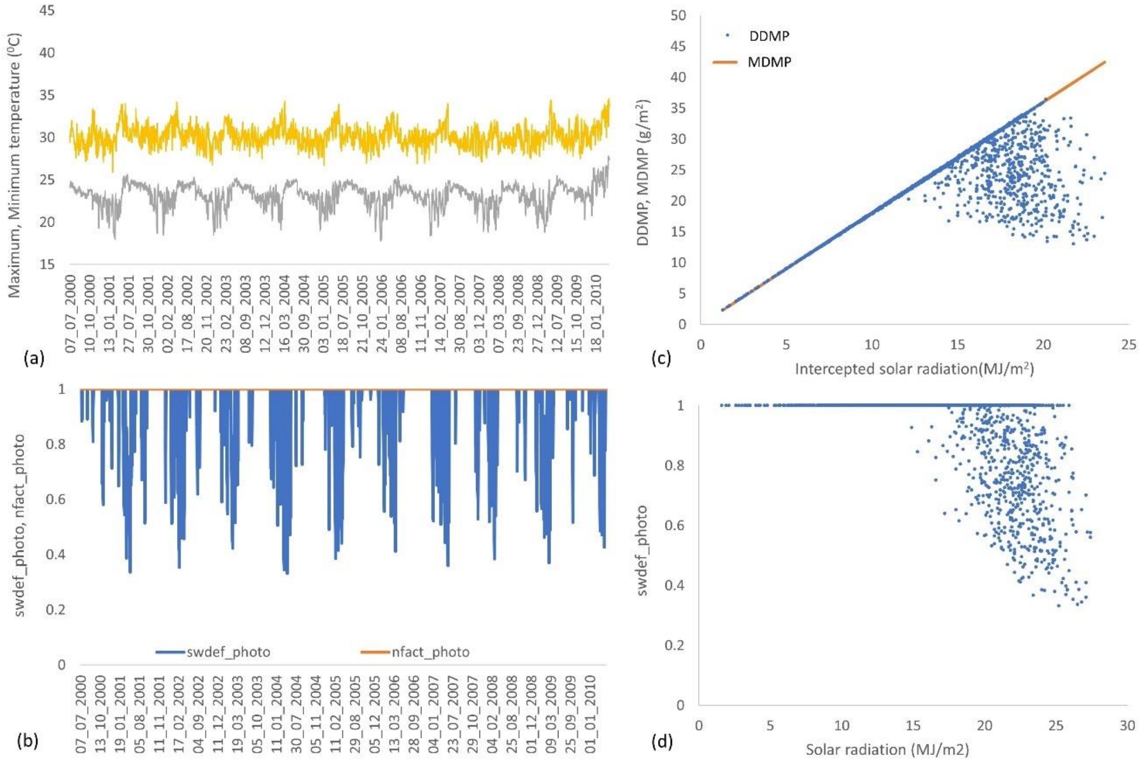

Figure 4.9. (a) Maximum and minimum temperature variation during crop stage 4 in Sri Lanka. (b) Soil water deficit (swdef_photo) and nitrogen deficit (nfact_photo) for photosynthesis of irrigated sugarcane (1 = no stress, 0 = full stress). (c) Relationship of intercepted solar radiation (MJ/m^2) with simulated daily dry matter production (DDMP; g/m^2) of irrigated sugarcane and calculated maximum possible daily dry matter production (MDMP; g/m^2) of sugarcane. (d) Relationship between solar radiation (MJ/m^2) and soil water deficit for photosynthesis of irrigated sugarcane.

4.3.4. Investigation of Interannual Variation in Parameter Influence

Sexton et al. (2017) found a 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 (Figure 4.4–4.7). 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 4.3). Considering climatic factors, we selected three growing seasons (Y2 2001–02, Y7 2006–07, Y10 2009–10) for comparison (Figure 4.10). 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/m^2) and cumulative potential ET (1688 mm). Y10 had the lowest cumulative solar radiation (6179 MJ/m^2) 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 three 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 more significant 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 2001–02, Y4 2003–04, and Y9 2008–09) for comparison (Figure 4.11). 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/m^2) and cumulative potential ET (1247 mm). Y2 had the lowest cumulative solar radiation (4690 MJ/m^2) and cumulative potential ET (1170 mm).

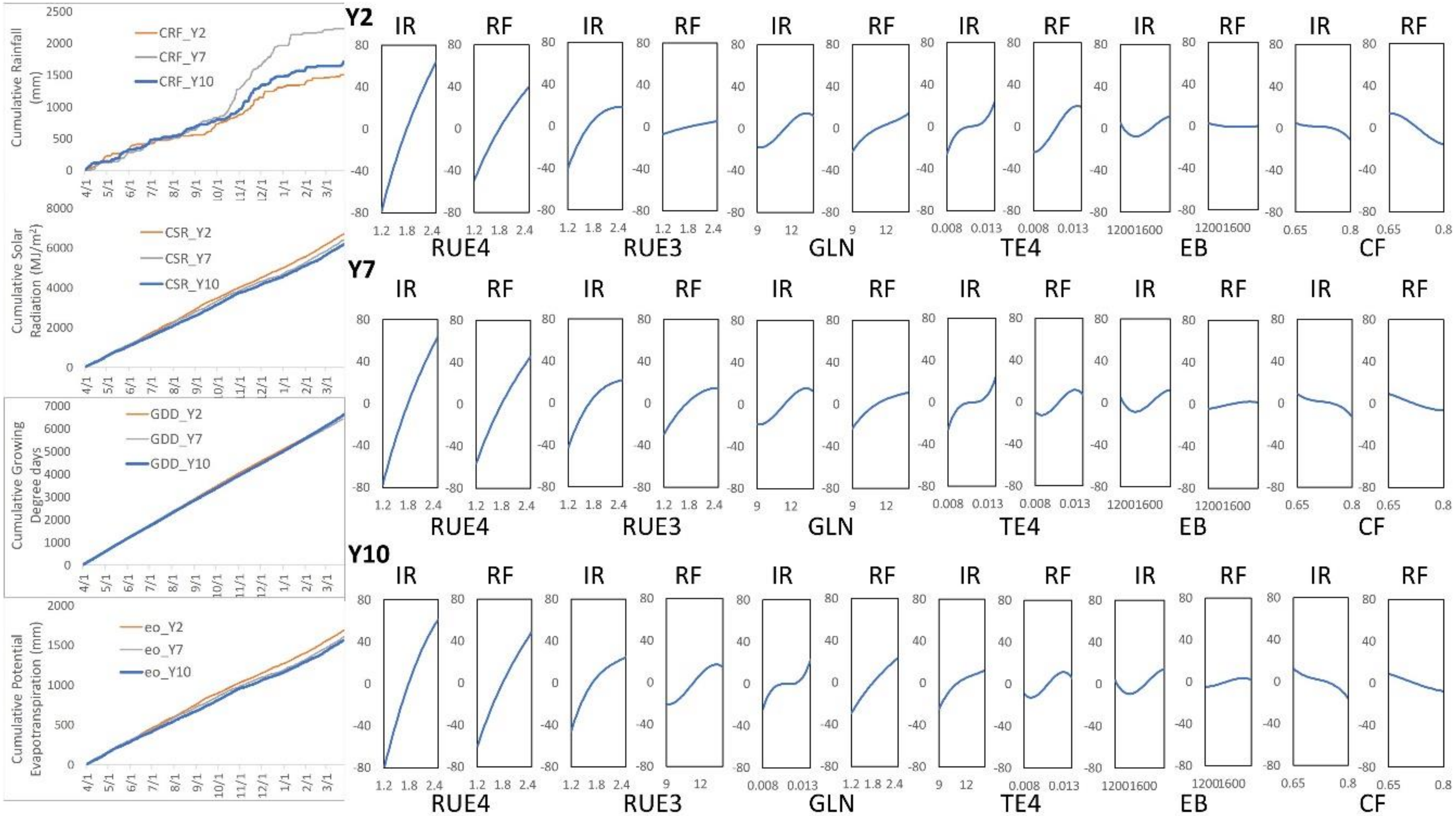

Figure 4.10. Depiction of interannual sensitivity variation of sugarcane in Sri Lanka: cumulative rainfall (mm), cumulative solar radiation (MJ/m^2), cumulative growing degree-days, cumulative potential evapotranspiration (mm), and parameter sensitivity variation among 2001–02, 2006–07, and 2009–10.

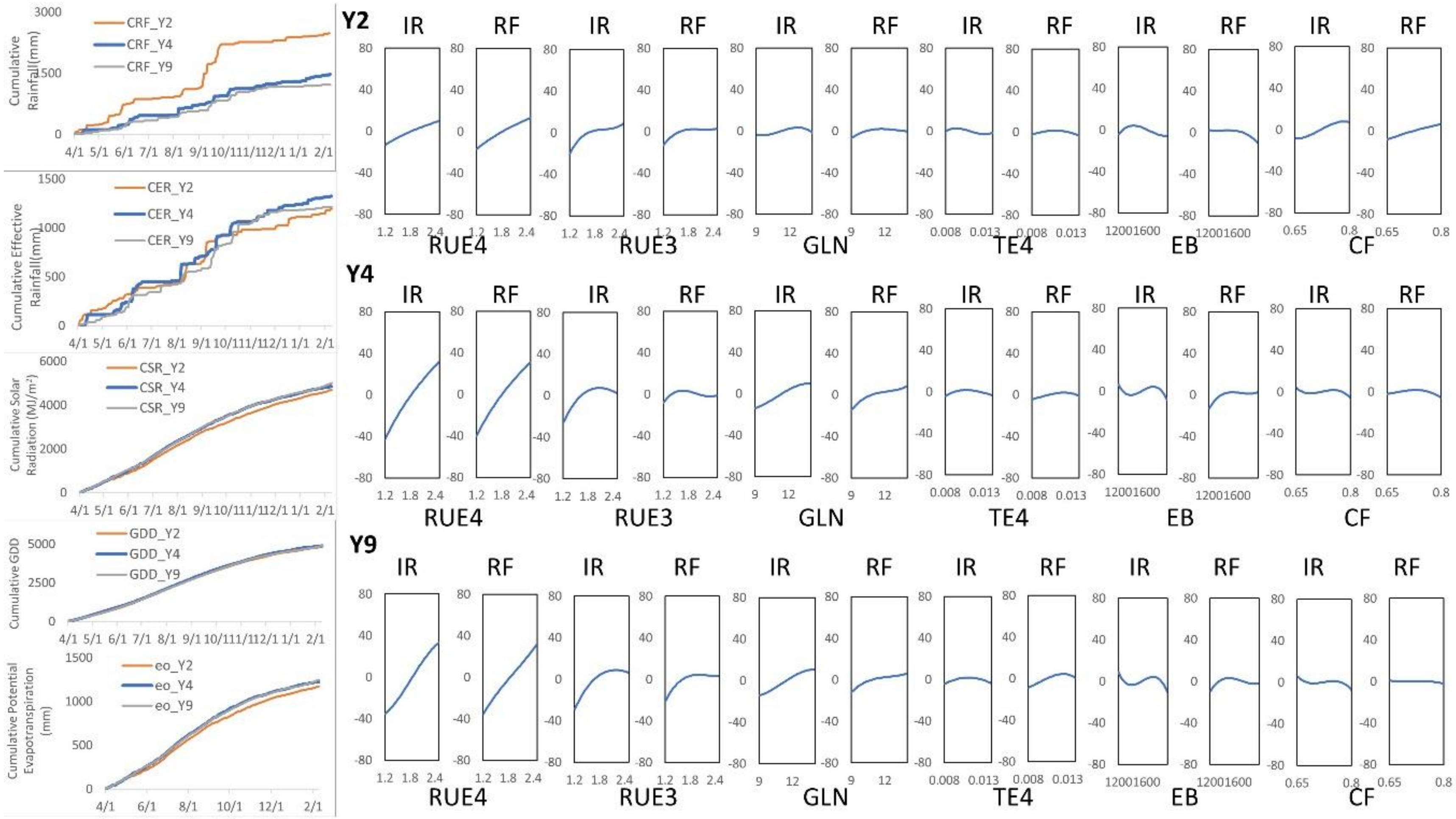

Figure 4.11. Depiction of interannual sensitivity variation of sugarcane in Okinawa: cumulative rainfall (mm), cumulative solar radiation (MJ/m^2), cumulative growing degree-days, cumulative potential evapotranspiration (mm), and parameter sensitivity variation among 2001–02, 2003–04, and 2008–09.

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.

4.3.5. Relationship between statistical dispersion and climatological parameters

We examined the statistical dispersion of emulator canefw outputs in response to climatic parameters (Figure 4.12). 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.

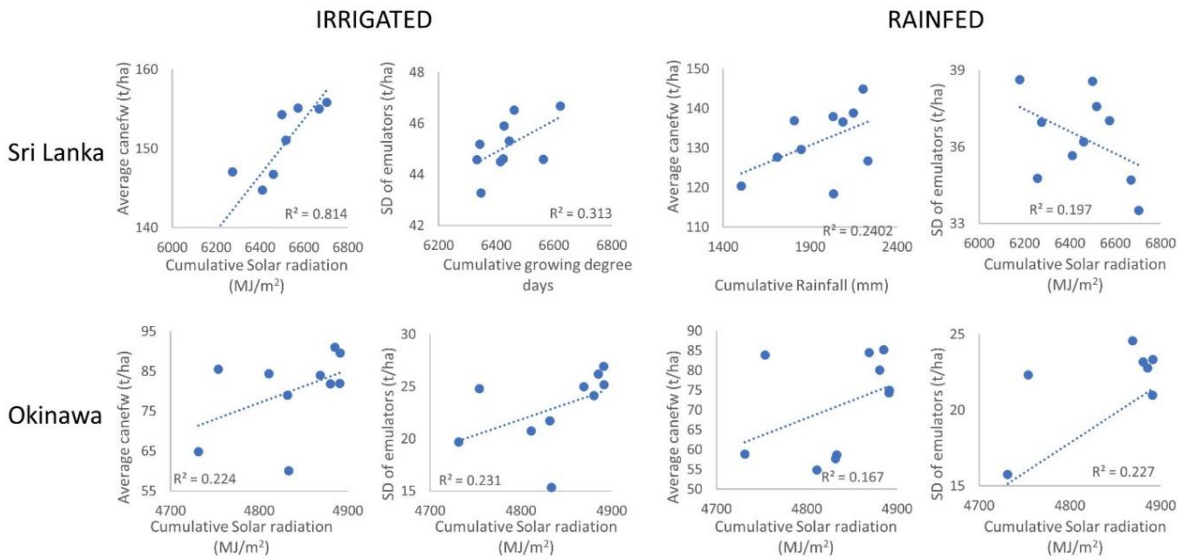

Figure 4.12. Relationships between average and SD of emulator canefw predictions with most closely related climatic conditions during the study period.

Solar radiation is a crucial 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. (2015) reported the higher sensitivity of sorghum yield to rainfall, solar radiation, and CO_2 in DSSAT simulations. Hence, solar radiation, rainfall, and temperature have the greatest influence on canefw in crop models.

4.4. 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 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 the 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 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 four 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 modeling of sugarcane growth and yield using APSIM.

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5.0 Simulation of growth and yield of sugarcane under OPSIS

5.1 Introduction

Optimized subsurface irrigation system (OPSIS) is a newly developed subsurface irrigation system to irrigate upland crops, such as sugarcane. In soils with low water holding capacity, OPSIS can show comparatively better performances than other irrigation methods. Solar-powered pump and minimum operational activities of OPSIS help to cut down operational costs of irrigation drastically, compared to the sprinkler irrigation, which is the common irrigation method of sugarcane in Okinawa, Japan (Gunarathna et al., 2017). When OPSIS is operating, water flows along the perforated OPSIS lines through the gravity. With the advancing water along the perforated OPSIS line, water can be moved to the outside soil, based on the water potential. As water moves outside, the soil becomes saturated. After that, outside soil and inside of the pipe come to an equilibrium. This equilibrium controls the amount and rate of irrigation. Further, the saturated layer starts to move the water upward due to the water potential created by matrix effects such as capillary action created via surface tension. As water moves upward, the moisture content of root zone soil increases and provide irrigation water to the crop (Gunarathna et al., 2017).

Using field experiments conducted in Itoman, Okinawa during 2013 to 2016, (Gunarathna et al., 2018) reported the advantages of OPSIS over sprinkler irrigation for sugarcane cultivation in Okinawa in respect of both sugarcane yield and WUE. However, they suggested conducting further validation of results using different assessment methods.

Crop simulation model is a vital tool with numerous uses, including the evaluation of different irrigation management practices. Well calibrated and validated crop model is a fast-alternative option for developing and evaluating agronomic practices (Saseendran et al., 2008). Hence crop models can act as a time and resource-saving option for researches on technological advances in agriculture. Different authors recorded the application of different crop models to evaluate irrigation methods and strategies. Saseendran et al., (2008) used CERES- maize model to determine the optimum allocation of limited irrigation between vegetative and reproductive growth stages and optimum soil water depletion level for initiating limited irrigation. Abd-El-Baki et al. (2017) used numerical crop model to determine the optimum irrigation depth for tomato crop. Kundu et al. (1982) used CORNGRO crop model to find out the optimum soil moisture depletion and replenishment levels and timing and amount of irrigation during different crop growth stages of corn. Mubeen et al. (2016) used CSM-CERES-Maize model to optimize the irrigation conditions.

Balwinder-Singh et al. (2016) used APSIM to evaluate the effect of mulch on the sowing date and irrigation management of wheat in Central Punjab, India. Sena et al. (2014) used APSIM to find out the optimum transplanting dates for achieving higher yield and water productivity of rice-wheat cropping systems in Middle IGP of India. Subash et al. (2014) evaluated the different irrigation regimes on rice-wheat cropping systems in IGP using APSIM model.

5.1.1 APSIM

APSIM (Agricultural Production Systems Simulator) is an open-source (for non-commercial users) crop modeling software, which can use to model growth and yield of many crops including sugarcane (Holzworth et al., 2014; Keating et al., 2003). Further, it has modeling functions, which allows simulating soil water, nutrients and many more (Holzworth et al., 2014; Inman-Bamber et al., 2016; Inman-Bamber and McGlinchey, 2003; Keating et al., 2003). Plant models in APSIM simulate major physiological processes such as phenology, water, and nutrient uptake, development of organs and responses for abiotic stresses, etc. Soil models in APSIM simulate water movements such as infiltration, capillary rise, evaporation, surface runoff, and drainage. Simple tipping bucket approach (SOILWAT module, (Probert et al., 1998)) and comprehensive numerical solution using Richard's equation (SWIM module, (Huth et al., 2012)) use to simulate water and solute movements. Further, it simulates soil organic matter decomposition and temperature changes (Holzworth et al., 2014). APSIM allows users to incorporate management interventions by own scripts written in scripting languages. Hence, it is a significant advantage in APSIM compared to other crop modeling software (Archontoulis et al., 2014; Holzworth et al., 2014). The uncertainties of predictions from this model are generally characterized by the error statistics determined from the prediction of experimental data. Therefore, firm parameterization, calibration, and validation are needed to reduce the uncertainties of predictions.

Therefore, this study aimed to develop the modeling capabilities of APSIM to evaluate the OPSIS. We conducted field experiments and modeling work to parameterize and calibrate the APSIM to simulate growth and yield of sugarcane. Further, we conducted field experiments and modeling work to validate the APSIM simulations of yield and growth of sugarcane under our newly developed irrigation method, optimized subsurface irrigation system (OPSIS). We evaluated the simulation accuracy of APSIM using different model evaluation criteria during both calibration and validation steps.

5.2 Materials and Methods

We conducted a series of field experiments to collect necessary data for parameterization and calibration of APSIM-sugar model for locally grown cultivar Ni21, which was developed to withstand against typhoons. Further, we conducted field experiments with the same cultivar to validate the APSIM to use with OPSIS. All the planting was done following the single-row planting method with 1.3 m spacing between the rows. We conducted all field experiments in farmer operated sugarcane fields located at Itoman, Okinawa, Japan (26^0 7' 59.07'' N, 127^0 40' 52.32'' E). The local climate is classified as Cfa by Köppen climate classification (Gima and Yoshitake, 2016; Rubel and Kottek, 2010).

5.2.1 Plant Data

We maintained two experimental plots as sprinkler irrigated, and OPSIS irrigated sugarcane fields grown with local cultivar Ni21. More information about the field experiments is presented by Gunarathna et al. (2018). We used the data obtained from sprinkler irrigated fields to parametrize and calibrate the APSIM-Sugar model while OPSIS irrigated fields to validate the APSIM to use with OPSIS. We conducted field experiments to observe growth and yield under two planting conditions—namely Spring and Summer planting following the local practice of Okinawa, Japan. We started the Spring planting in April 2013 and harvested in March 2014. The crop extended to observe the growth and yield of two consecutive ratoon crops which were harvested in January 2015 and January 2016. We started summer planting in October 2013 and harvested in January 2015. We extended only the OPSIS irrigated the crop to observe the growth and yield of first ratoon crop, and it was harvested in January 2016. Following the regular fertilizer application practice in Okinawa, we used 350 kg/ha of urea fertilizer for the main crop and ratoon crops for both irrigation methods. For sprinkler irrigation, we added fertilizer in 31 and 62 days after planting or harvesting. We applied the same amount of fertilizer for the OPSIS, however, as a ten-split application during the first 3 months through the OPSIS.

We randomly selected a 5.2 m^2 area to estimate the fresh cane yield of the spring- and summer-planted main crops and the two ratoon crops. At the harvesting, further, we counted stalks per unit area to calculate stalk densities of different crops. Although, the plant height not used in many studies to calibrate or validate the APSIM sugar model, we used plant height due to the unavailability of other parameters for the evaluation. We measured the plant height of the summer-planted main crop and the first ratoon crop of the spring-plant at monthly intervals from May 2014 to January 2015 as the distance from the soil surface to the +1 dewlap (de Sousa et al., 2015). We used first and second ratoons of Spring planting to evaluate the soil moisture dynamics and irrigation water use of crops under OPSIS.

5.2.2 Soil Data

We used soil samples from six layers as 0-10, 10-20, 20-30, 30-40, 40-50 and 50-60 cm to estimate the lower limit (LL15, mm/mm), drained upper limit (DUL, mm/mm), soil saturation (SAT, mm/mm), bulk density (BD, g/cm^3), particle density (TD, g/cm^3) and saturated hydraulic conductivity (KS, mm/day). LL15 and DUL were considered as the volumetric water content equilibrium to the -1500 kPa and -33 kPa respectively and was measured using the centrifuge method. Measured BD and TD values were used to estimate soil saturation. Saturated hydraulic conductivity was estimated in the laboratory using the constant head method. Further, soil samples were analyzed to estimate soil pH, NO3-N, NH4-N levels, and soil carbon. We created a new soil profile for Itoman, Okinawa, and parameterized using the measured data (Table 5.1).

Table 5.1. Soil data used to parameterize Itoman soil profile

Depth (cm)	Bulk Density (g/cc)	Air Dry (mm/mm)	LL15 (mm/mm)	DUL (mm/mm)	SAT (mm/mm)	KS (mm/day)	Sugar LL (mm/mm)
0-10	1.107	0.100	0.277	0.422	0.481	7827	0.277
10-20	1.154	0.100	0.295	0.415	0.48	19712	0.295
20-30	1.310	0.100	0.298	0.453	0.484	10834	0.298
30-40	1.197	0.100	0.300	0.447	0.496	4432	0.300
40-50	1.237	0.100	0.310	0.436	0.511	814	0.310
50-60	1.264	0.100	0.290	0.428	0.522	800	0.290

Soil moisture levels were measured in 5, 15, 25, 35, 45, and 55 cm depths using soil moisture sensors (5TE, Decagon Devices, Pullman, WA, USA) in OPSIS field to evaluate the soil moisture dynamics of OPSIS.

5.2.3 Irrigation water use

We measured the irrigation water use of the 1st and 2nd ratoon crops of spring-plant which were irrigated using OPSIS. Flow meters attached to the outlet and inlet of the water column of the OPSIS were used to estimate the daily irrigation amount through the OPSIS.

5.2.4 Climatological data

Daily maximum and minimum temperature, precipitation, radiation, wind speed, pressure and relative humidity values of Naha, Okinawa, Japan were obtained from Japan metrological agency website (www.jma.go.jp/jma/menu/report.html) for the period of 1/1/1980 to 31/08/2016. Annual average ambient temperature and annual amplitude in mean monthly temperature were calculated using tav_amp utility software of APSIM (https://www.apsim.info/Products/Utilities). A new met was parameterized using the data above.

5.2.5 APSIM-OPSIS module

We scripted a new module named "OPSIS" to couple optimized subsurface irrigation system to the APSIM engine. The fifth layer was selected as the base layer, where the OPSIS is located. The difference between the SAT and the soil water content (SW) of the layer is identified as the input to the layer. It is the estimated amount of irrigation through the optimized subsurface irrigation and named as "opsis (mm/day)".

5.2.6 APSIM Simulation

APSIM, the Agricultural Production Systems sIMulator is a process-based dynamic crop model that combines biophysical and management modules within a central engine to simulate diverse cropping systems (Holzworth et al., 2014; Keating et al., 2003). The model is driven by daily climate data and can simulate growth, development, and yield of crops and their interactions with soil.

First, we modified the sugar model of APSIM 7.10 by adding new cultivar Ni21. Then we parameterize the cultivar parameters using the data obtained from field measurements, published reports on Ni21 cultivar, and experts' views (Table 5.2).

Table 5.2. Cultivar and plant specific parameters used to parametrization and calibration of APSIM-Sugar model

Parameter	Initial values (parameterization)		Values used for simulations (after calibration)	
	Crop	Ratoon	Crop	Ratoon
Leaf_size 1, 14, 20	2000, 48000, 48000	2000, 48000, 48000	2000, 48000, 48000	2000, 48000, 48000
cane_fraction	0.7	0.65	0.7	0.7
Sucrose_fraction_stalk 0.2, 1	1.0, 0.5	1.0, 0.5	1.0, 0.5	1.0, 0.5
sucrose_delay	0	0	0	0
min_sstem_sucrose	800	800	800	800
min_sstem_sucrose_redn	10	10	10	10
tt_emerg_to_begcane	1800	1800	1900	1900
tt_begcane_to_flowering	6000	6000	6000	6000
tt_flowering_to_crop_end	2000	2000	2000	2000
green_leaf_no	13	13	13	13
tillerf_leaf_size 1, 4, 10, 16	1.5, 1.5, 1.5, 1	1.5, 1.5, 1.5, 1	1.5, 1.5, 1.5, 1	1.5, 1.5, 1.5, 1
rue	0, 0, 1.80, 1.80, 1.80, 0	0, 0, 1.65, 1.65, 1.65, 0	0, 0, 2.00, 2.00, 2.00, 0	0, 0, 1.85, 1.85, 1.85, 0
Crop_height_max	6000	6000	4000	4000

Then, we simulated the spring planted and summer planted sugarcane growth and yield under sprinkler irrigation from March 2013 to January 2016 and September 2013 to January 2015, respectively. As APSIM underestimated the growth and yield, we modified the RUE like-minded Gunarathna et al. (2019) and Sexton et al. (2017). Dias et al. (2019) also suggested substantial changes to enable APSIM-Sugar to simulate canopy and yield for Brazilian genotypes. We increased the maximum RUE values up to 2.0 confining the findings of De Silva and De Costa (2012) and Muchow et al. (1997). Similarly, we increased the maximum RUE values of ratoon crop up to 1.85 conforming the gap maintained by APSIM. As Ni21 is developed to withstanding against typhoon conditions, plants usually do not show higher plant heights. Hence, we limited the maximum plant height up to 4000 mm from the default of 6000 mm. Further, we calibrated cane fraction (CF) and thermal time from emergence to beginning of cane (EB) by trial and error method to find the optimum values for those parameters (Table 5.2).

Then, we simulated the spring planted (from March 2013 to January 2016) and summer planted (from September 2013 to January 2016) sugarcane growth and yield under OPSIS. We used fresh cane weight at harvesting, plant heights of first ratoon crop of spring-plant and main crop of summer-plant, soil moisture levels of top five layers and irrigation water use through the OPSIS to validate the application of APSIM with OPSIS. During the summer of the year 2015, there were several typhoons were occurred, and substantial crop damages were observed. Therefore, after considering the field observations, historical yield records, and experts' views, the observed yield of second ratoon of spring plants (both sprinkler and OPSIS irrigated crops) and first ratoon of summer plant were adjusted by adding 20% of observed yield to the observed yield.

5.2.7 Model Evaluation

We used different model evaluation criteria such as root mean square error (RMSE; Equation 5.1), mean absolute error (MAE; Equation 5.2), coefficient of determination (R^2; Equation 5.3) and Wilmott's agreement index (d; Equation 5.4) (Willmott, 1981) to evaluate the simulation accuracy (Dias and Sentelhas, 2017; Krause et al., 2005). Low RMSE and MAE values indicate good agreement between model outputs and observed values, while high R^2 and d also assure the same. The Lin's concordance correlation coefficient (CCC) integrates precision through Pearson's correlation coefficient, which represents the proportion of the total variance in the observed data that can be explained by the model, and accuracy by bias which indicates how far the regression line deviates from the concordance line (Ojeda et al., 2017). CCC ranges from -1 to 1, with the perfect agreement at 1. It can legitimately calculate accuracy with few observations for agreement on a continuous measure obtained by two methods (Stevenson et al., 2018). We calculated the CCC using epiR package (Stevenson et al., 2018) of R software (R Core Team, 2018).

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{\mathrm{i}=1}^{\mathrm{n}}(\mathrm{S_i} - \mathrm{O_i})^2} \tag{5.1}$$

$$MAE = \frac{1}{n}\sum_{\mathrm{i}=1}^{\mathrm{n}}|\mathrm{S_i} - \mathrm{O_i}| \tag{5.2}$$

$$R^2 = \left[\frac{\sum_{i=1}^{n}(O_i-\bar{O})(S_i-\bar{S})}{\sqrt{\sum_{i=1}^{n}(O_i-\bar{O})^2}\sqrt{\sum_{i=1}^{n}(S_i-\bar{S})^2}}\right]^2 \tag{5.3}$$

$$d = 1 - \frac{\sum_{i=1}^{n}(S_i - O_i)^2}{\sum_{i=1}^{n}(|S_i - \bar{O}| + |O_i - \bar{O}|)^2} \tag{5.4}$$

Where, S_i and O_i are the simulated and observed value of the parameter (in fresh cane yield (t/ha), plant height (mm), soil moisture (mm/mm) irrigation water (mm/month) respectively; $\bar{O}$ and $\bar{S}$ are the average of simulated and observed values respectively; and n is the number of observations.

5.3 Results and Discussion

5.3.1 Parameterization and calibration of APSIM-Sugar to simulate growth and yield of cultivar Ni21

Initially, we added cultivar Ni21 to the APSIM-Sugar model (XML file) and parameterized using field measured data (leaf size and green leaf number), available data in published reports, and views of experts (Table 5.2). After the parameterization, we simulated fresh cane weight and plant height. We observed quite healthy relationships between observed and simulated values. However, APSIM underestimated the fresh cane weight. After the modification of plant parameters (maximum RUE and maximum plant height of main and ratoon crops) and calibration of cultivar parameters (CF and EB), the relationships were further improved (Figure 5.1). Despite of the high variability of cane yield and sucrose affected by weather conditions, nutrient levels, planting time and some undefined factors, APSIM sugarcane able to simulate good results to fit with the observations in agreement with the results of Keating et al. (1999), Cheeroo-Nayamuth et al. (2000) and Inman-Bamber and McGlinchey (2003). Using data sets of different cultivars grown in different locations, Keating et al. (1999) showed that APSIM could simulate the millable stalk weight (R^2= 0.72, RMSD = 1.94 t/ha) with fairly good accuracy. Inman-Bamber et al. (2016) showed the better predictive ability of APSIM-sugar model after modifying the transpiration efficiency and root water supply. Our study also proves the virtuous ability of APSIM to simulate fresh cane weight as all model evaluation criteria shows a good fit between simulations and observations (RMSE = 3.195 t/ha, R^2 = 0.93, MAE = 2.74 t/ha). Further, plant height simulations, also showed good agreement with the observations (RMSE = 493 mm, R^2 = 0.87, MAE = 397 mm).

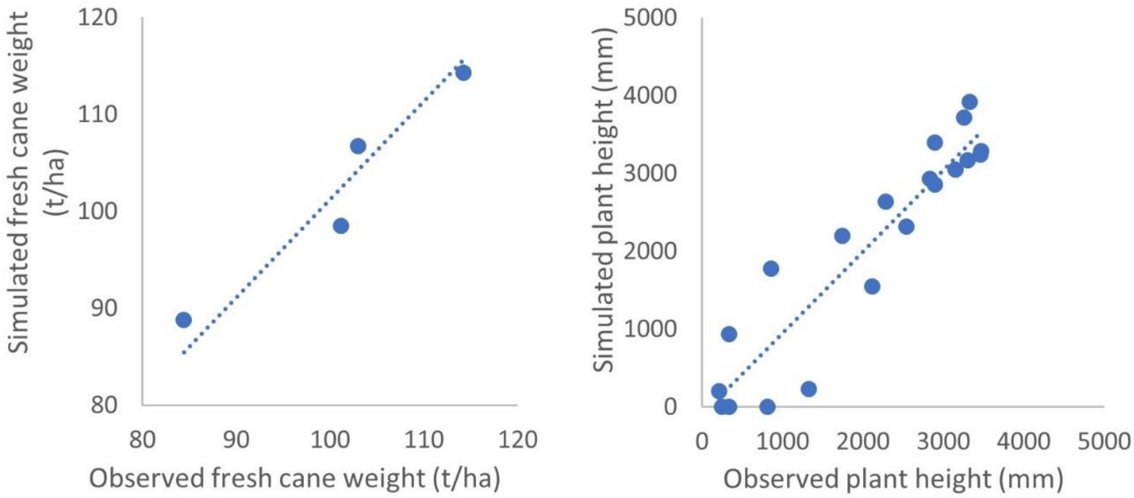

Figure 5.1. Observed versus simulated a) fresh cane weight; b) plant height of sugarcane cultivar Ni21

In this study, we used higher maximum RUE values than the APSIM usually used. Although it is not a usual practice in APSIM crop modeling studies, we change the maximum RUE values to minimize the gap between simulate and observed values with higher input conditions with novel genotypes. However, we believed that the APSIM may not use the maximum RUE values always as it is controlled by soil moisture status, nutrient availability and reduced growth phenomenon (RGP) (Park et al., 2005). RGP reduces RUE, with highly favorable environment conditions as highly favorable conditions may lead lodging (Park et al., 2005; van Heerden et al., 2015).

5.3.2 Validation of APSIM to simulate growth and yield of cultivar Ni21 under OPSIS

We simulated the fresh cane weight and plant height of sugarcane cultivar Ni21 under OPSIS using newly parameterized and calibrated APSIM-sugar model and APSIM-OPSIS module. Results revealed that APSIM simulations show good agreement with observed fresh cane yield and plant height. Further, observed soil moisture dynamics and irrigation water use also showed acceptable agreement between simulated values.

5.3.2.1 Plant height

In summer-planted sugarcane, APSIM with OPSIS showed a good simulation of plant height (Figure 5.2). Although it was slightly underestimated during the latter part, model evaluation criteria confirmed that simulation is almost similar to the observations (Table 5.3). In the first ratoon of spring-planting observed and simulated plant heights diverged each other as APSIM sugarcane under simulated the plant height in early stages of the crop (Figure 5.3). However, in late stages, the first ratoon of spring plant showed higher growth rate in simulation compared to the observed, therefore, during the harvesting, simulated plant height became slightly higher (4%) than the observed value. Although the simulation accuracy is not good as summer plant, model evaluation criteria confirmed that simulation is comparable with observations (Table 5.3). Further, Table 5.3 confirmed that plant height simulation of summer-planted main crop is better than the results of the calibration study, while first ratoon crop of spring-plant showed slightly poor performances compared to the calibration results.

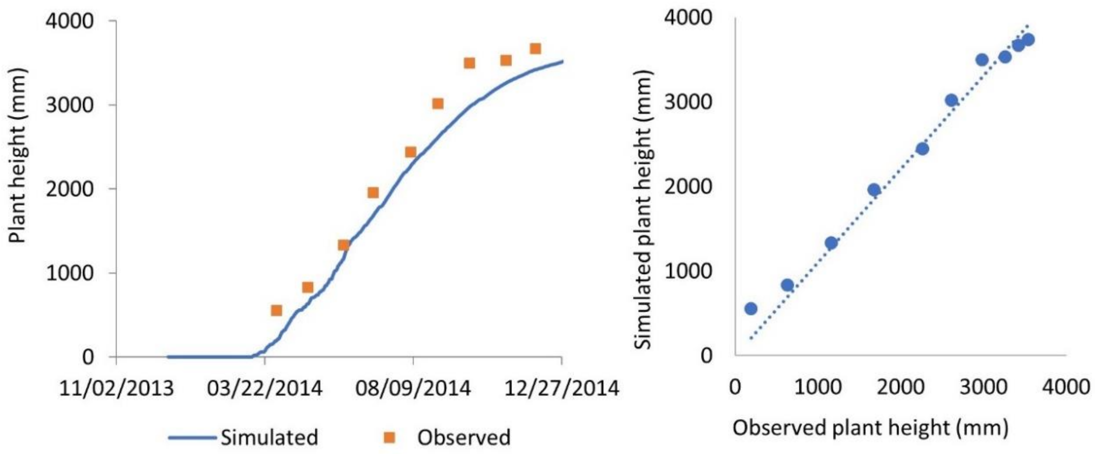

Figure 5.2. Observed versus simulated plant height of summer-planted sugarcane crop

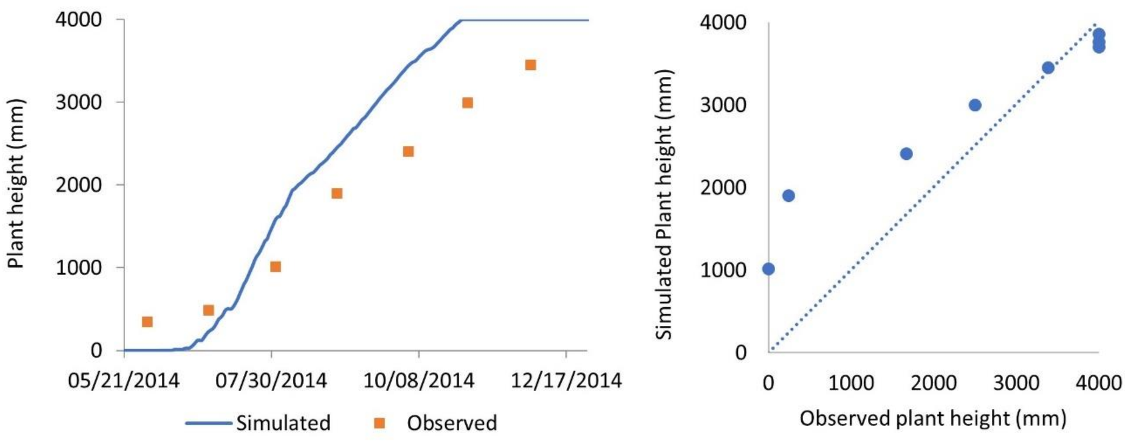

Figure 5.3. Observed versus simulated plant height of spring-planted first ratoon crop

Table 5.3. Evaluation of simulation accuracy of APSIM with OPSIS

Variable (unit)	Planting season (Crop/ratoon)	Model evaluation criterion				
		R^2	*MAE	*RMSE	d	CCC
Fresh cane yield (t/ha)	All	0.82	4.67	6.08	0.64	0.56
Plant height (mm)	Summer planting (Crop)	0.99	286	306	0.98	0.97
	Spring planting (1st ratoon)	0.96	582	769	0.91	0.85
Average soil moisture of root zone (mm/mm)	Spring planting (1st ratoon)	0.32	0.047	0.052	0.49	0.28
	Spring planting (2nd ratoon)	0.50	0.053	0.056	0.45	0.21
Monthly irrigation water use (mm/month)	Spring planting (1st ratoon)	0.01	11.19	13.18	0.47	0.91
	Spring planting (2nd ratoon)	0.22	15.51	17.45	0.27	0.84

*Unit is equal to the unit of the variable

5.3.2.2 Fresh cane weight

Confirming the virtuous ability of APSIM to simulate fresh cane weight, APSIM under OPSIS simulated fresh cane yield with good agreement to the observations (Figure 5.4) as all model evaluation criteria shows a good fit between simulations and observations (Table 5.3). The RMSE value reported (6.08 t/ha) is far enough for a simulation study as it is about 5% of the average observed fresh cane yield. R^2 (0.82) and d (0.64) also confirmed the goodness of fit between observed and simulated fresh cane yield. Further, these validation results are equally good as the results of the calibration study. Similarly, Mao et al. (2018) showed the ability of locally calibrated APSIM-sugar to simulate cane yield with a high level of accuracy.

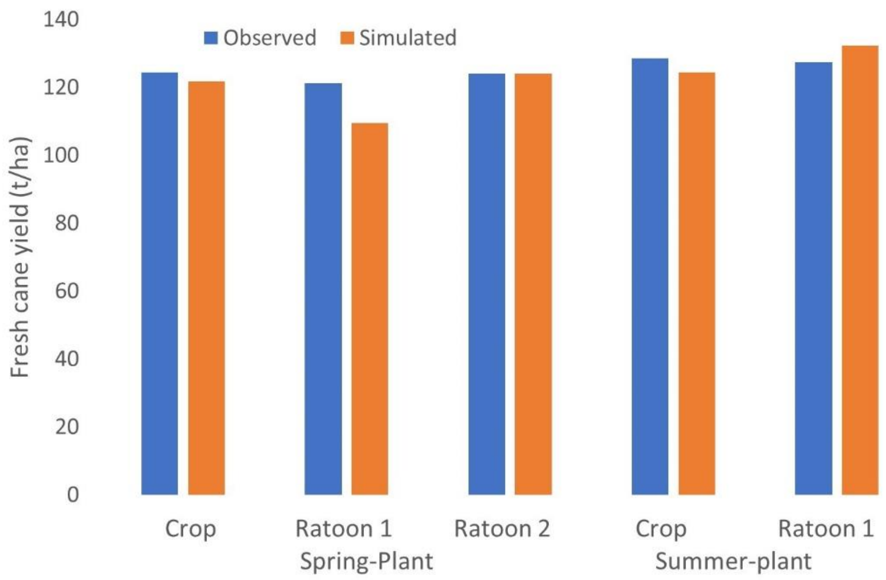

Figure 5.4. Comparison of the observed and simulated yield of sugarcane under OPSIS

5.3.2.3 Soil moisture dynamics

Figure 5.5 shows the variation of predicted and observed soil moisture levels in different layers of the soil during the first and second ratoons of spring planting. The results showed that APSIM had overpredicted the soil moisture levels, especially the upper part of the root zone. Since the soil water movements are much complicated; it is difficult to acquire precise simulations from simple model predictions. In this study, we used a cascading layer approach to estimate the soil water movements. However, this is a simple approach; hence, it may not be able to simulate the soil water movements accurately. Similarly, overestimation of APSIM simulated soil moisture in upper levels and quite good simulations in lower layers has been reported by Balwinder-Singh et al. (2011). In a crop simulation study, Marin et al. (2011) reported that calibrated DSSAT/Canegro simulated soil water content with reasonably good accuracy as they observed mean RMSE as 0.214 mm. Archontoulis et al. (2014) reported the ability of APSIM to simulate the soil water dynamics with reasonable accuracy as they reported the RMSE of prediction is 0.032 mm/mm. Sena et al. (2014) also observed higher error between observed and simulated soil moisture, then they calibrated the soil parameters to minimize the error of soil moisture simulations.

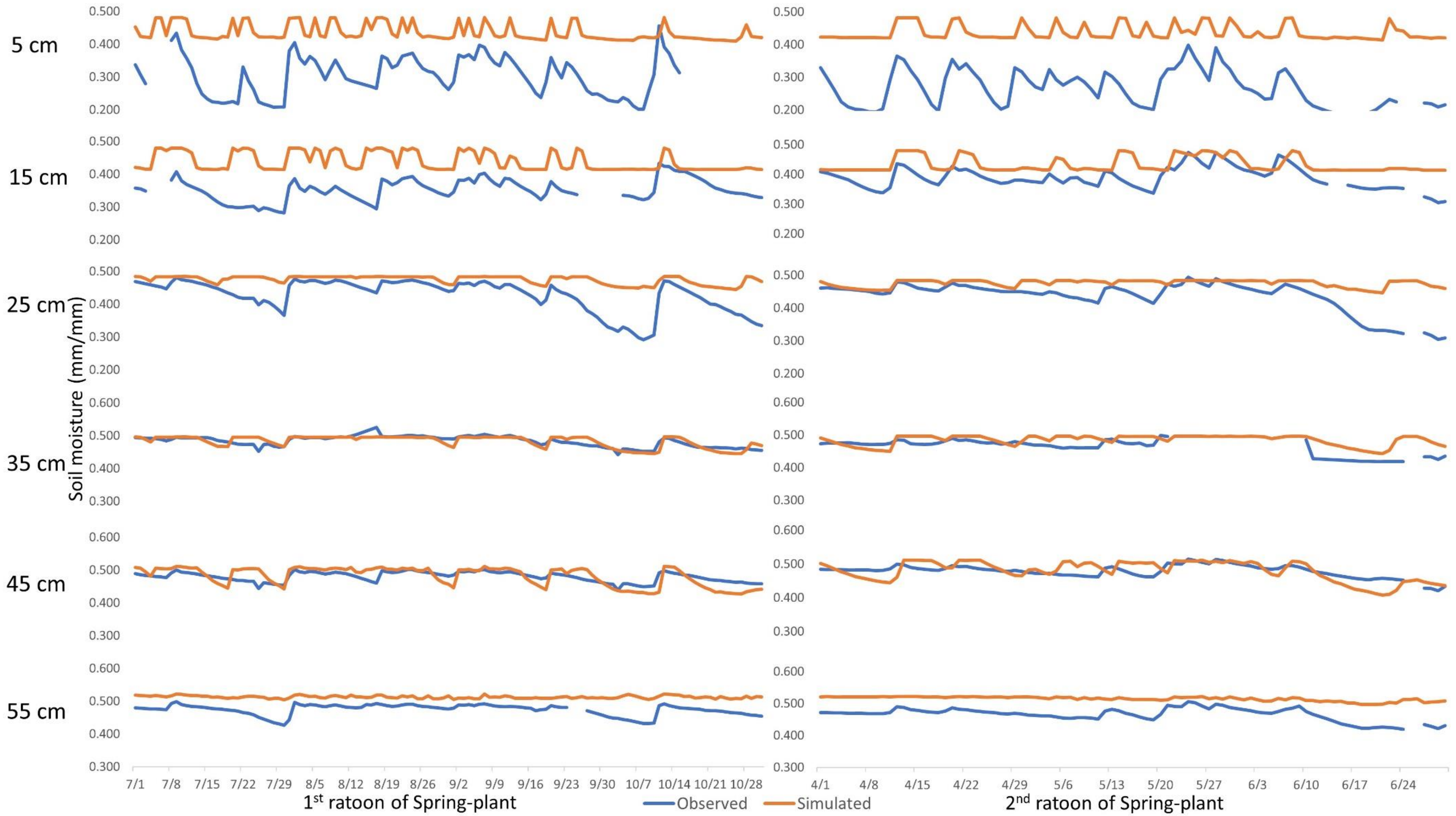

Figure 5.5. Observed and simulated soil moisture variation different layers of the soil during the first and second ratoon crop of spring-plant

The SOILWAT module able to make a fair prediction of soil water dynamics in OPSIS operated sugarcane fields. The overestimation of soil moisture content in the top layers, maybe due to differences in simulated and actual daily soil evaporation rates and over the capillary rise and lower downward movements controlled by saturated flow parameter (SWCON). The origin of these differences requires further investigation. Therefore, a study focused on comprehensive measurements is required to acquire accurate modeling of soil water dynamics. Brown et al. (2018) proposed a comprehensive model (WEIRDO, Water Evapotranspiration Infiltration Redistribution Drainage runOff) to simulate soil water dynamics. However, this model only works with APSIM next generation. In this study, we used the classical version of APSIM (APSIM 7.10); therefore, we unable to use this model. This model may able to comprehend the soil moisture dynamics of OPSIS irrigated fields. Therefore, we are suggesting to study the applicability of this model in future studies.

5.3.2.4 Irrigation water use

The relationship between the observed and simulated amount of water irrigated as OPSIS during the first ratoon crop of spring-planting are shown in figure 5.6. Similar to the moisture levels in the soil, APSIM overpredicted the irrigation water use by OPSIS.

No studies to compare the irrigation water use (IWU) as typically APSIM do not simulate the irrigation amount. In this study, we simulated the IWU applied through our newly designed irrigation system named as OPSIS. Model evaluation criteria (Table 5.3) show that the simulations are not comparable with observed irrigation amount. However, the MAE values show that the estimated errors are 11.2 and 15.5 mm/month for first and second ratoon crops, respectively. Application of the comprehensive model to simulate soil moisture dynamics may rectify the error of irrigation water predictions as IWU depends on the crop water uses as well as soil evaporation and percolation losses.

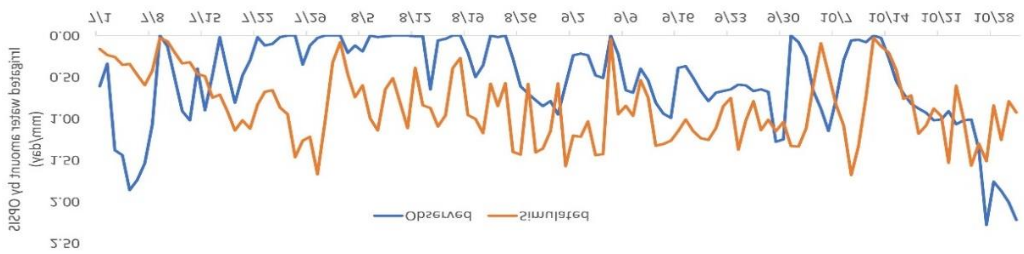

Figure 5.6. Observed versus simulated irrigation water use through OPSIS of spring-planted first ratoon crop

5.4 Conclusions and Recommendations

We modified the APSIM-Sugar model to simulate growth and yield of sugarcane cultivar Ni21, which was developed to withstand against the strong winds of typhoons. Then we parameterize the cultivar Ni21 using measured values, information published in reports, and expert's views. However, APSIM underestimated the growth and yield of sugarcane cultivar Ni21 under Okinawan conditions. Therefore, the APSIM-Sugar model was modified and calibrated using radiation use efficiency, thermal time from emergence to the beginning of cane and cane fraction. After the calibration, APSIM simulations showed a close relationship with the observations. Then, we validated the APSIM to use with OPSIS. We developed APSIM-OPSIS module to couple OPSIS with APSIM engine. The simulation results were comparable with the observations. Simulated plant height and fresh cane yield showed good agreement with the observations. However, APSIM showed overestimation for soil water content in upper soil layers and irrigation water use of OPSIS.

Hence, newly developed APSIM-OPSIS module can successfully be used to simulate the crop growth and yield of sugarcane with optimized subsurface irrigation system. Although it gives quite reasonable results, further studies are suggested to develop the simulation accuracy of soil water dynamics and irrigation water use through the OPSIS.

5.5 References

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6.0 Pedotransfer Functions to Estimate Hydraulic Properties of Tropical Sri Lankan Soils

This chapter is based on Gunarathna, M.H.J.P., Sakai, K., Nakandakari, T., Momii, K., Kumari, M.K.N., Amarasekara, M.G.T.S., 2019. Pedotransfer functions to estimate hydraulic properties of tropical Sri Lankan soils. Soil Tillage Res. 190, 109–119. https://doi.org/10.1016/j.still.2019.02.009

6.1. Introduction

Estimates of soil hydraulic properties are essential in environmental management and agriculture. Data on soil hydraulic properties are rising in importance with the rapid increase of agricultural automation and the increasingly sophisticated models that support modern agriculture (Patil and Singh, 2016). However, direct measurements of these properties by field and laboratory methods are laborious, expensive, and time-consuming (Minasny and Hartemink, 2011; Rustanto et al., 2017). Thus the development of inexpensive, rapid indirect methods to estimate soil hydraulic properties is an area of active research (Pachepsky and Rawls, 2003; Patil and Singh, 2016; Tomasella and Hodnett, 2004).

Pedotransfer functions (PTFs) are predictive functions used to estimate difficult-to-measure soil parameters based on more easily measurable soil parameters (Bouma, 1989). Point-based PTFs are used to estimate soil parameters at specific, conventional values of matric potential (Patil and Singh, 2016). The moisture content at –10 and –33 kPa, representing field capacity, and moisture content at –1500 kPa, representing a permanent wilting point, are the most common reference values used for point-based PTFs (Botula et al., 2014; Patil and Singh, 2016). Methods of developing point-based PTFs have mainly taken regression approaches (Nguyen et al., 2015), which have been successfully used to develop PTFs to estimate specific points on the moisture retention curve (Adhikary et al., 2008; Botula, 2013; Liao et al., 2011; Mdemu, 2015; Minasny and Hartemink, 2011). More recently, machine-learning approaches have gained popularity in PTF development, including artificial neural networks (Jana and Mohanty, 2011; Minasny et al., 2004; Nemes et al., 2003), k-nearest neighbor (Botula et al., 2013; Mihalikova et al., 2014; Nemes et al., 2006), and random forest approaches (Rodríguez-Lado et al., 2015; Souza et al., 2016). However, linear models offer superior ease of use, parsimony, interpretability, and computational efficiency (Hastie et al., 2009). Therefore, we used a method based on linear regression to develop PTFs in this study.

As populations continue to proliferate in tropical regions, food insecurity, soil degradation, climate change, and water scarcity pose increasing threats to agriculture, the environment, and human livelihoods. Although the crop, irrigation, and environmental modeling are active fields of research worldwide, modeling efforts in the tropics have been limited by the availability of soil data (Gaydon et al., 2017; Kang et al., 2009). Irrigation modeling tools, for instance, require soil hydraulic data to determine schedules (timing and quantity) for irrigation applications. Although various techniques and tools have been developed to prepare irrigation schedules, most lands, especially in tropical regions, are irrigated on fixed schedules for lack of relevant data. Typically, farmers apply set amounts of irrigation water without first making a site-specific assessment of irrigation timing and depth, which penalizes yield and causes losses in water, energy, nutrients, and soil (Liang et al., 2016).

In the absence of usable data, farmers in tropical regions often use PTFs developed for temperate soils, even though extrapolating PTFs to different regions is problematic (Minasny and Hartemink, 2011; Patil and Singh, 2016; Tomasella and Hodnett, 2004). Such is the case in Sri Lanka. Other than one attempt to evaluate the applicability of point-based PTFs developed in other tropical environments to dry-zone soils in Sri Lanka (Gunarathna and Sakai, 2018), no PTFs have been developed for Sri Lankan soils (Botula et al., 2014).

6.1.1. Objectives of the study

In this study, we aimed to develop PTFs to estimate volumetric water content (VWC) in tropical Sri Lankan soils at –10, –33, and –1500 kPa by using linear regression methods similar to most previous efforts elsewhere. In light of the limited laboratory facilities and research budgets in most tropical countries, we investigated PTFs developed using different sets of input parameters to evaluate the minimum input data needed for acceptable performance.

Although extensive research exists on using PTFs to estimate soil hydraulic properties from readily available soil properties, very few studies have gone further to evaluate the functionality of these PTFs in field-level applications, where they can assist soil-plant-atmospheric modeling by generating input data at low cost and with low risk of gross model error (Nemes et al., 2010). Therefore, this study further aimed to test the functionality of these PTFs in field-level applications by comparing the output of the PTFs to measured values relevant to water content estimates and irrigation scheduling.

6.2. Materials and methods

This study was based on a dataset of soil samples collected during the comprehensive soil survey of Sri Lanka conducted under the SRICANSOL project (Dassanayake et al., 2010, 2005; Senarath et al., 1999). This survey contains information on land use, taxonomic, physical, and chemical properties of 110 soil profiles (including soil horizon level information) covering almost all soil series and land uses in Sri Lanka (lowland and upland agricultural fields, plantations, forests, bare lands, residential areas, and so on) except those in the northern part of the country (Figure 6.1) (Dassanayake et al., 2010, 2005; Senarath et al., 1999). For this study we used sand percentages measured by sieve analysis, silt and clay percentages measured by the pipette method, bulk densities measured from undisturbed core samples 5.4 cm in diameter and 6 cm high, organic carbon percentages measured using the Walkley-Black method, and VWC measured at –10, –33, and –1500 kPa by the pressure plate method using undisturbed soil samples 5.4 cm in diameter and 3 cm high. Samples with missing VWC data were removed from consideration, leaving 323 samples for the study. Descriptive statistics of selected parameters are listed in Table 6.1, and Figure 6.2 shows a ternary plot of the sand, silt, and clay percentages of selected soils. These data were used to develop PTFs for tropical Sri Lankan soils under five different sets of input data: sand only (Set 1), sand, silt, and clay (Set 2), Set 2 plus bulk density (Set 3), Set 3 plus organic carbon (Set 4), and Set 4 plus soil structural class (Set 5) (Table 6.2). Because soil structure did not emerge as an essential attribute when estimating the three VWC values, we ignored Set 5 in the following analysis.

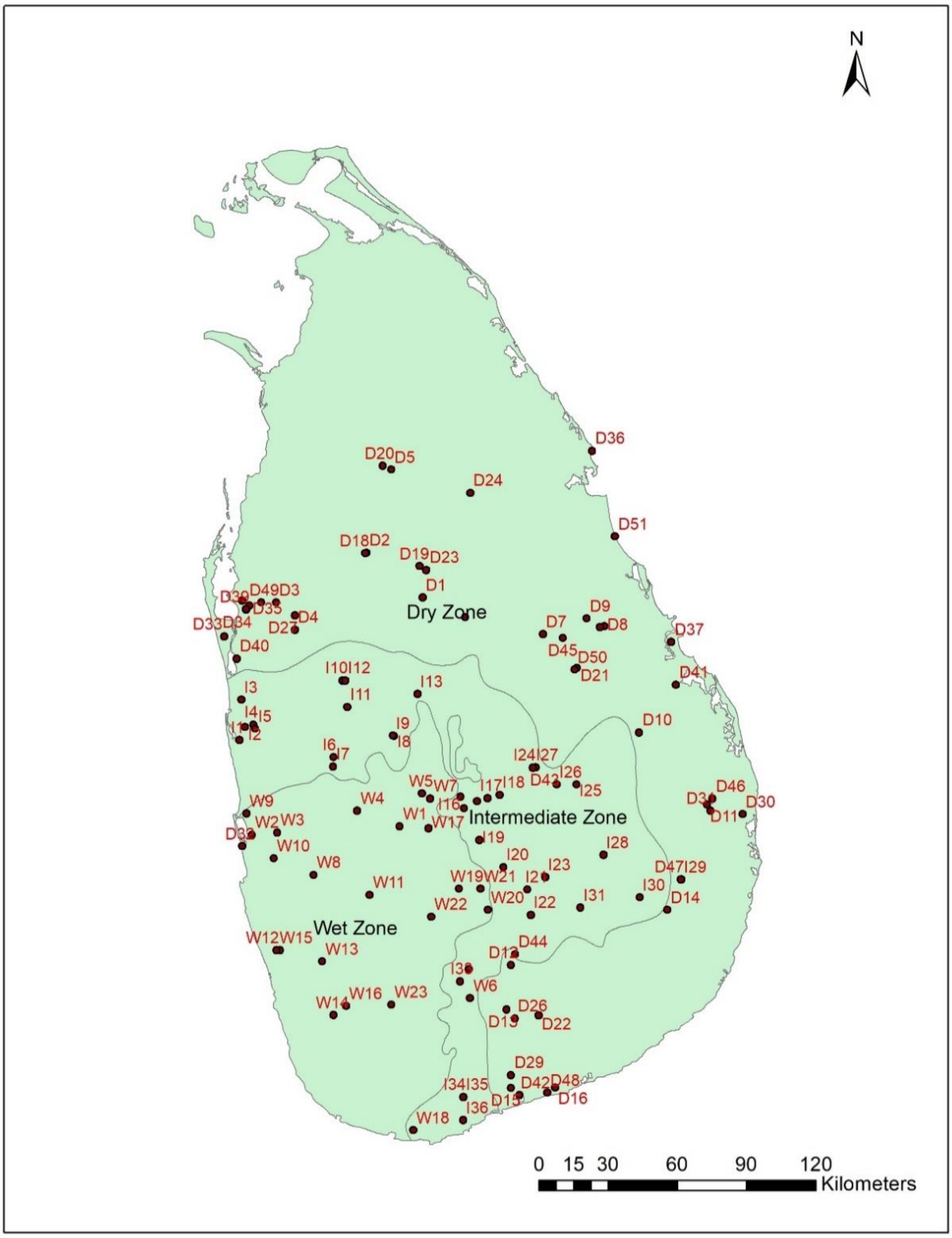

Figure 6.1. Distribution of 110 soil sampling locations selected for the study

Table 6.1. Summary statistics of selected soils of Tropical Sri Lanka

	VCS (%)	CS (%)	MCS (%)	FS (%)	VFS (%)	SA (%)	SI (%)	CL (%)	BD (g/cm^3)	OC (%)	VWC10	VWC33	VWC1500
Minimum	0.0	0.4	1.6	6.1	0	5.2	0.0	1.0	1.0	0.0	0.06	0.04	0.02
Maximum	57.9	47.6	52.9	56	62.9	99.0	38.6	61.4	2.0	4.5	0.54	0.47	0.45
Mean	12.1	22.3	24.3	24.7	16.6	65.1	13.1	21.9	1.49	0.6	0.24	0.21	0.15
SD	10.8	9.5	9.7	8.7	12.3	17.4	7.7	13.2	0.17	0.6	0.09	0.08	0.07

VCS – Very coarse sand; CS – Coarse sand; MCS – Medium coarse sand; FS – Fine sand; VFS – Very fine sand; SA – Sand; SI – Silt; CL – Clay; BD – Bulk density; OC – Organic carbon; $VWC_{-x\ kPa}$ - Volumetric water content at -10, -33 and -1500 kPa; SD – Standard deviation

Table 6.2. Selected basic attributes, added attributes and selected attributes after the evaluation of different input levels

Input level	Basic attributes used	Added attributes	Selected attributes after evaluation	Output
Set 1	SA	SA^2	SA	VWC10
			SA	VWC33
			SA	VWC1500
Set 2	SA, SI, CL	(SA*SI), (SA*CL), (SI*CL), SA^2, SI^2, CL^2	SA, SI	VWC10
			SA, SI	VWC33
			SA	VWC1500
Set 3	SA, SI, CL, BD	(SA*SI), (SA*CL), (SI*CL), SA^2, SI^2, CL^2, BD^2	SA, SI, BD, BD^2	VWC10
			SA, SI, BD, BD^2	VWC33
			SA, BD, BD^2	VWC1500
Set 4	SA, SI, CL, BD, OC	(SA*SI), (SA*CL), (SI*CL), SA^2, SI^2, CL^2, BD^2, OC^2	SA, SI, BD, OC, BD^2, OC^2	VWC10
			SA, SI, BD, BD^2, OC^2	VWC33
			SA, BD, BD^2, OC^2	VWC1500
Set 5	SA, SI, CL, BD, OC, ST	(SA*SI), (SA*CL), (SI*CL), SA^2, SI^2, CL^2, BD^2, OC^2	SA, SI, BD, OC, BD^2, OC^2	VWC10
			SA, SI, BD, BD^2, OC^2	VWC33
			SA, BD, BD^2, OC^2	VWC1500

SA – Sand; SI – Silt; CL – Clay; BD – Bulk density; OC – Organic carbon; ST – Soil texture; VWC10, VWC33, and VWC1500 - Volumetric water content at -10, -33 and -1500 kPa

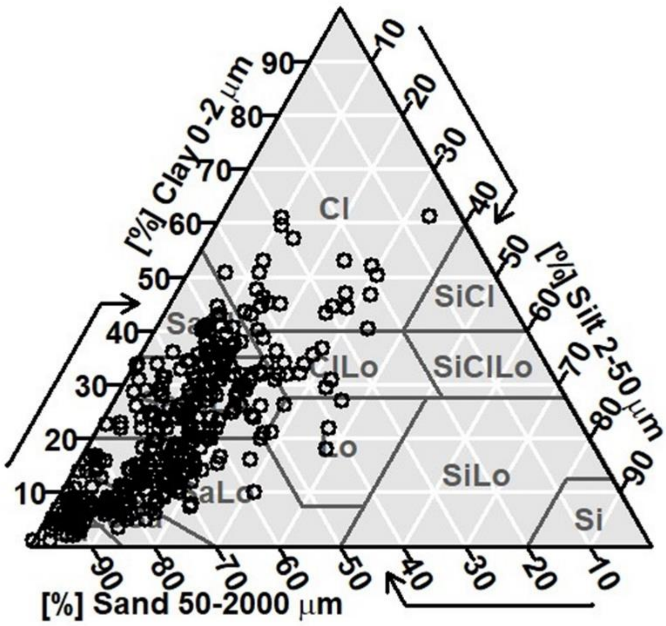

Figure 6.2. Ternary plot of the sand, silt, and clay percentages of 323 soil horizons selected for the study

6.2.1. WEKA software

The Waikato Environment for Knowledge Analysis (WEKA) is a Java-based open-source data mining tool developed by the University of Waikato, New Zealand that provides an interface to run different learning algorithms with different preprocessing and postprocessing options (Frank et al., 2016; Hall et al., 2009). WEKA includes cross-validation as a technique to evaluate predictive models by partitioning the input data into a training set to train the model and a test set to evaluate it. We chose tenfold cross-validation as the test option for this study, in which the sample data were randomly divided into ten equal subsamples. Nine of these are used to train the model, and the remaining one is used to test the model. This process is repeated ten times, with each subsample used once as the testing data. The results are then averaged to produce a single estimation (Pachepsky and Schaap, 2004).

6.2.1.1 Attribute selection

Attribute selection is a procedure that searches all possible combinations of attributes in a dataset to find the combination that yields the best prediction. The selection process is based on an attribute evaluator and a search method. The CfsSubsetEval function in WEKA was used as the attribute evaluator. This function is a correlation-based feature selector that evaluates the worth of a subset of attributes by considering the individual predictive ability of each feature along with the degree of redundancy between them (Hall, 1999). The search method chosen was GreedyStepwise (forward), which performs a greedy forward search through the space of attribute subsets, starting from a single attribute and ending when the addition of another attribute reduces the model fit. The attributes selected at each level of this analysis are listed in Table 6.2.

6.2.1.2 Multiple linear regression

Multiple linear regression (MLR) is commonly used for the prediction of a response variable (y) from a set of predictor variables (Vereecken and Herbst, 2004):

$$y = a + \sum_{i=1}^{n} b_i x_i + \varepsilon, \tag{6.1}$$

where a is an intercept, x_i is a predictor variable, b_i is a regression coefficient, and ε represents the error. MLR methods are widely used, owing to their ease of application, to develop PTFs (Botula et al., 2014). In WEKA, stepwise MLR with the backward elimination function was used for this study (weka.classifiers.functions.LinearRegression). Collinear attributes were eliminated by enabling the Remove collinear attribute function (as the default), and all other attributes remained at their defaults in WEKA 3.8. WEKA uses the Akaike information criterion (AIC) to select the best model fit (Frank et al., 2016).

6.2.2 Model evaluation

We assessed the predictive capabilities of the PTFs developed by different methods in terms of the following statistical functions (Patil and Singh, 2016) in WEKA:

$$r = \frac{1}{n-1} \sum_{i=1}^{n} \frac{(M_i - \overline{M})(E_i - \overline{E})}{S_M S_E} \tag{6.2}$$

$$\text{MAE} = \sum_{i=1}^{n} \frac{|E_i - M_i|}{n} \tag{6.3}$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (E_i - M_i)^2}{n}} \tag{6.4}$$

$$\text{RAE} = \frac{\sum_{i=1}^{n} |E_i - M_i|}{\sum_{i=1}^{n} |\overline{M} - M_i|} \times 100 \tag{6.5}$$

$$\text{RRSE} = \sqrt{\frac{\sum_{i=1}^{n} (E_i - M_i)^2}{\sum_{i=1}^{n} (\overline{M} - M_i)^2}} \times 100 \tag{6.6}$$

where r is the correlation coefficient, MAE is the mean absolute error, RMSE is the root mean squared error, RAE is the relative absolute error, RRSE is the root relative squared error, n is the number of data instances used for modeling, M_i is the measured target value, E_i is the estimated target value, $\bar{M}$ is the mean of measured target values, $\bar{E}$ is the mean of estimated target values, S_M is the sum of measured target values, and S_E is the sum of estimated target values. Each criterion was considered separately, and the success of the PTFs was evaluated by their performance relative to that of MLR.

A two-sample t-test was used to check the statistical significance of measured and estimated values, using R software (R Core Team, 2016). The F test was used to compare the variances of the two samples, and a t-test assuming equal or unequal variances was used accordingly. The AIC (Akaike, 1974) was used to evaluate the performance of the PTFs developed using MLR with different inputs:

$$\text{AIC} = n\log(\frac{\text{RSS}}{n}) + 2K \,, \tag{6.7}$$

where K is the number of independently adjusted parameters within the model, n is the sample size, and RSS is the residual sum of squares (Burnham and Anderson, 2002). We also used the Diebold-Mariano test (Diebold and Mariano, 1995) to compare the accuracies of PTFs developed from sand percentage alone, and PTFs developed from different sets of input attributes, using the forecast package of R (Hyndman, 2017; Hyndman and Khandakar, 2008). PTFs developed using different input combinations were compared based on regression error curves and residual density plots using the auditor package of R (Gosiewska and Biecek, 2018).

6.2.3 Model application

Applications of PTF models in earth system sciences include estimating soil water contents and flows, root zone hydraulic processes, hydraulic parameters of land surface models, solute transport processes, soil carbon and nutrient cycling processes, and process-based crop models (Van Looy et al., 2017). The applications we tested for this study were the estimation of total plant-available moisture content of the root zone, readily available moisture content of the root zone, and irrigation scheduling, using CROPWAT 8.0.

CROPWAT 8.0 for Windows decision support software is developed by the Food and Agriculture Organization (FAO) to estimate crop and irrigation water demands based on climatological data (monthly mean maximum and minimum temperature, relative humidity, sunshine duration, wind speed, and rainfall), crop data (crop coefficients, rooting depth, and percentage plant cover), and soil data (maximum infiltration rate, rooting depth, initial moisture, and available soil moisture). CROPWAT is also used to develop irrigation schedules under different management conditions and crop patterns. Our calculations followed two FAO publications in the Irrigation and Drainage Series, No. 33 on the yield response to water (Doorenbos and Kassam, 1979) and No. 56 on crop evapotranspiration (Allen et al., 1998). CLIMWAT, an associated FAO database, provides long-term monthly average climatic data from 3262 meteorological stations in 144 countries (Wahaj et al., 2007). The outputs of CROPWAT include reference evapotranspiration, crop water requirement, irrigation water requirement (gross and net), actual evapotranspiration, soil moisture deficit, estimated yield reduction due to stress, and irrigation schedule.

6.2.3.1 Estimation of available water content

Most irrigation models and software used in precision agriculture are dependent on real-time soil moisture measurements and estimates of total or readily available water that are based on measured or estimated field capacity and permanent wilting point values. We estimated the total available water (the difference between moisture content at –33 kPa and –1500 kPa) of selected soil horizons using measured and PTF-derived data. We also estimated the readily available water in the root zone at 75 cm depth in selected soil profiles using both measured and PTF-derived data and assuming 70% as the depletion level. We conducted a functional evaluation of the PTFs that was based on comparing measured and PTF-derived values of total available water in selected soil horizons and readily available water in selected soil profiles.

6.2.3.2 Estimation of irrigation water requirement

Maize is the second-largest crop in Sri Lanka in terms of cultivated area, cultivated in upland areas mainly during the Maha season (October to February, during the northeast monsoon) with or without supplementary irrigation and in the Yala season (April to

August, during the southwest monsoon) with supplementary irrigation. We used CROPWAT to estimate the irrigation water requirement of the maize crop for both cultivation seasons in Sri Lanka. Considering the climatic data available in the CLIMWAT 2.0 database and the availability of nearby soil profiles, we selected soil profiles from six localities (Badulla, Batticaloa, Hambantota, Puttalam, Trincomalee, and Vavuniya) to calculate the irrigation water requirement of maize. Climate/evapotranspiration and rainfall files for these locations were downloaded from CLIMWAT 2.0. Maize was selected as the crop, and planting dates were set at 1 April for the Yala season and 1 October for the Maha season. All other values (crop growth stages and crop coefficients) were set at their defaults. Soil files were prepared using measured and PTF-derived values of total available soil moisture. We used these inputs to estimate the net irrigation requirement and irrigation dates for both growing seasons at these locations, and then studied the functionality of the PTFs for field applications using those irrigation schedules.

6.3. Results and discussion

6.3.1 Development of PTFs

When we used MLR to develop a set of PTFs to estimate VWC at –10, –33, and –1500 kPa with different sets of input attributes (Table 6.3), our evaluation showed that adding bulk density and organic carbon percentage to the models only slightly improved their performances, and the Diebold-Mariano test showed that this increment was not significant at the p = 0.05 level. Furthermore, the AIC values showed that these two parameters added appreciably to the computational cost while not notably improving the model fit. Residual density plots (Figure 6.3) and regression error curves (Figure 6.4) also confirmed these results. Previous studies have confirmed the ability of PTFs developed from soil textural data to predict VWC of tropical soils (Adhikary et al., 2008; Botula, 2013; Dijkerman, 1988; Lal, 1979). However, some studies have found that bulk density and organic carbon percentage were useful additions to the same analysis with fine-textured soils (Gaiser et al., 2000; Minasny and Hartemink, 2011; van den Berg et al., 1997).

Botula (2013) and Dijkerman (1988) developed PTFs that used the sand percentage as the sole input variable to estimate the field capacity, but not the permanent wilting point. Table 6.3 shows that our PTFs based on sand percentage alone (Set 1) predicted VWC of Sri Lankan soils well. Typical Sri Lankan soils have relatively large proportions of sand

(Table 6.1 and Figure 6.2), most of which are categorized as fine or very fine sand (Table 6.2). This may explain the relationship of the sand percentage to the water holding capacity of Sri Lankan soils because the sand percentage is very strongly correlated with VWC (Table 6.4). Furthermore, Sri Lankan soils show a robust linear relationship over the range of VWCs considered (Figure 6.5), such that sand percentage alone is enough to satisfactorily estimate field capacity and permanent wilting point. It appears that even with the minimal equipment needed to measure sand percentage (2 mm and 0.05 mm sieves, H_2O_2, Calgon solution, and an electric mixer) (Dharmakeerthi et al., 2007), field capacity and permanent wilting point can be estimated using these PTFs with acceptable accuracy. In developing regions, poor data availability is a major barrier to using crop models (Gaydon et al., 2017; Gunda et al., 2017; Kang et al., 2009; Zubair et al., 2015). Therefore, sand-only PTFs appear to offer acceptable solutions for crop and environment modelers in Sri Lanka. All statistical indicators confirmed that the PTFs developed using sand alone estimate VWC roughly as well as PTFs that incorporate multiple input variables. However, it is advisable to use multiple inputs, if available, to estimate VWC to minimize the possible risk of 100% erroneous due to the sand percentage as a sole input.

Table 6.3. Pedotransfer functions (and performances) developed using multiple linear regression method for different input levels

Set	R	MAE	RMSE	RAE	RRSE	T	DM	AIC	Equation
VWC at -10 kPa									
1	0.7016	0.0469	0.0637	67.673	70.951	NS	-	-770.60	VWC10 = 0.4802 - 0.0037*SA
2	0.7198	0.0464	0.062	66.866	69.041	NS	0.407	-773.70	VWC10 = 0.3967 - 0.0029*SA + 0.0025*SI
3	0.7186	0.0467	0.0621	67.277	69.215	NS	0.848	-770.04	VWC10 = 0.4436 - 0.0028*SA + 0.0024*SI - 0.034*BD
4	0.7238	0.046	0.0617	66.275	68.699	NS	0.510	-772.34	VWC10 = 0.3951 - 0.0029*SA + 0.0023*SI + 0.0052*OC^2
VWC at -33 kPa									
1	0.7219	0.0436	0.0577	65.102	68.843	NS	-	-797.34	VWC33 = 0.4357 - 0.0035*SA
2	0.7286	0.0434	0.0571	64.777	68.149	NS	0.188	-798.78	VWC33 = 0.3701 - 0.0029*SA + 0.0020*SI
3	0.7294	0.0439	0.057	65.511	68.06	NS	0.370	-795.70	VWC33 = 0.4236 - 0.0028*SA + 0.0018*SI - 0.0388*BD
4	0.7318	0.0434	0.0568	64.678	67.82	NS	0.563	-796.93	VWC33 = 0.3686 - 0.0029*SA + 0.0018*SI + 0.0046*OC^2
VWC at -1500 kPa									
1 2	0.7415	0.0336	0.0464	62.213	66.784	NS	-	-857.42	VWC1500=0.3426 - 0.003*SA
3	0.746	0.034	0.046	62.51	66.29	NS	0.664	-857.50	VWC1500 = 0.6397 - 0.0028*SA - 0.385*BD + 0.1169*BD^2
4	0.7624	0.0327	0.0448	60.605	64.413	NS	1.574	-863.56	VWC1500= 0.3278 - 0.0028*SA + 0.0082*OC^2

r - Correlation coefficient; MAE - mean absolute error; RMSE - root mean squared error; RAE - relative absolute error; RRSE - root relative squared error; T (t-test within the set) - NS – Measured and estimated values are not significantly difference at p=0.05 level; DM - Diebold-Mariano Test For Predictive Accuracy (* denoted significantly different predictions compared to the PTF developed using sand as only predictor variable) ;SA – Sand; SI – Silt; CL – Clay; BD – Bulk density; OC – Organic carbon; VWC10, VWC33 and VWC1500 - Volumetric water content at -10, -33 and -1500 kPa

Table 6.4. Pearson's correlation matrix between soil properties of Sri Lankan soils

	Sand (%)	Silt (%)	Clay (%)	BD	OC	VWC10	VWC33	VWC1500
Sand (%)	-	***	***	***	***	***	***	***
Silt (%)	-0.70	-	***	***	***	***	***	***
Clay (%)	-0.91	0.34	-	***	*	***	***	***
BD	0.43	-0.41	-0.33	-	***	***	***	***
OC	-0.18	0.25	0.09	-0.33	-	***	***	***
VWC10	-0.71	0.61	0.58	-0.38	0.21	-	***	***
VWC33	-0.73	0.60	0.61	-0.40	0.21	0.97	-	***
VWC1500	-0.75	0.58	0.65	-0.40	0.29	0.91	0.93	-

BD – Bulk density; OC – Organic carbon; VWC10, VWC33 and VWC1500 - Volumetric water content at -10, -33 and -1500 kPa; *, ** and ***: correlation is significant at p<0.1, p<0.05 and p<0.01

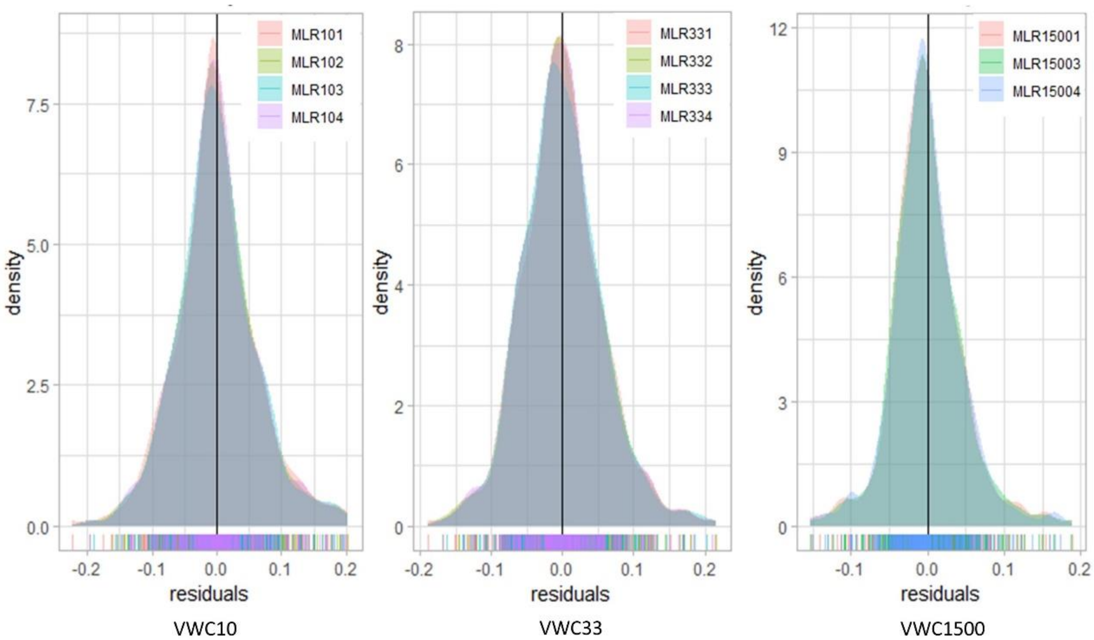

Figure 6.3. Residual density plots of PTFs developed using different input levels

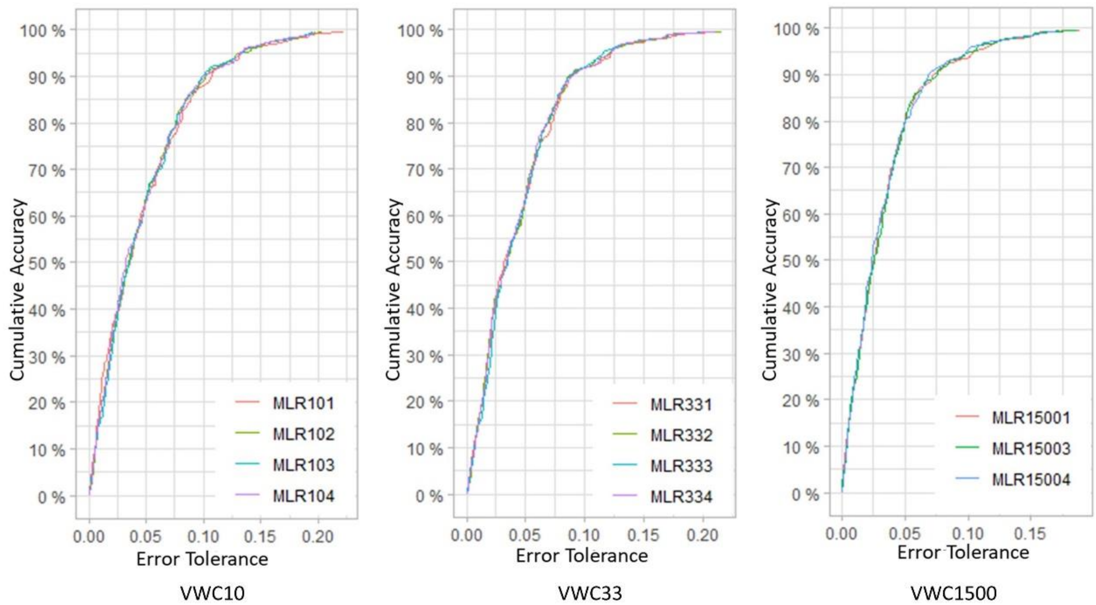

Figure 6.4. Regression error curves of PTFs developed using different input levels

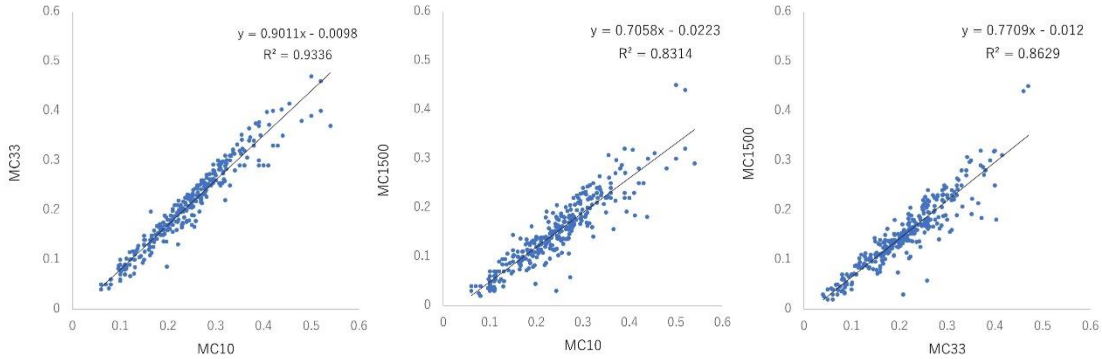

Figure 6.5. The relationship between the selected volumetric water contents

The dataset used for this study consisted of tropical soils from dry, wet, and intermediate climatic zones as well as sandy, loamy, and clay soils. We considered the three classes of sandy, loamy, and clay (Minasny et al., 1999) because some textural classes were inadequately represented in our sample. Therefore, we examined the possible effect of the climatic zone and soil type on the prediction ability of our PTFs. Figure 6.6 shows that the PTFs produced fairly good predictions in all climatic regions and soil types, a finding also reported by Minasny et al. (1999). Our PTFs, therefore, appear to be applicable across the whole range of Sri Lankan tropical soils and climatic regions.

However, irrespective of the climatic zone or soil type, our PTFs slightly overpredicted VWCs with higher sand percentages. Figure 6.7 confirms that PTFs slightly overestimated VWC at –10, –33, and –1500 kPa when the sand percentage exceeded 64%, 66%, and 66%, respectively.

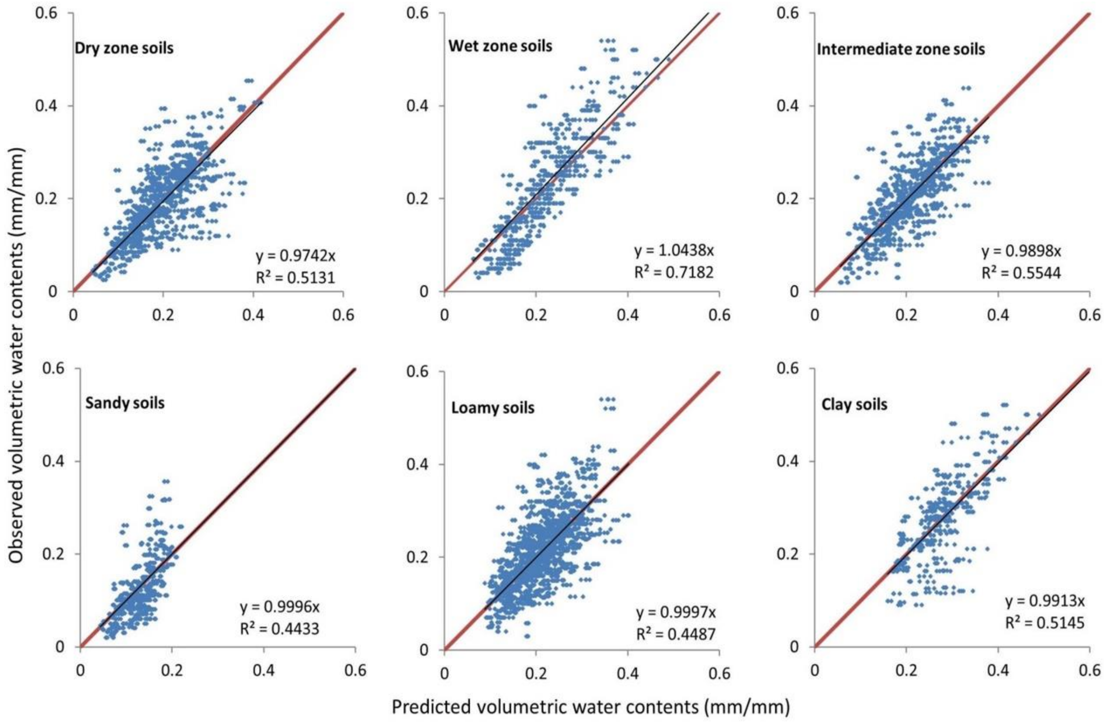

Figure 6.6. Observed and predicted volumetric water contents

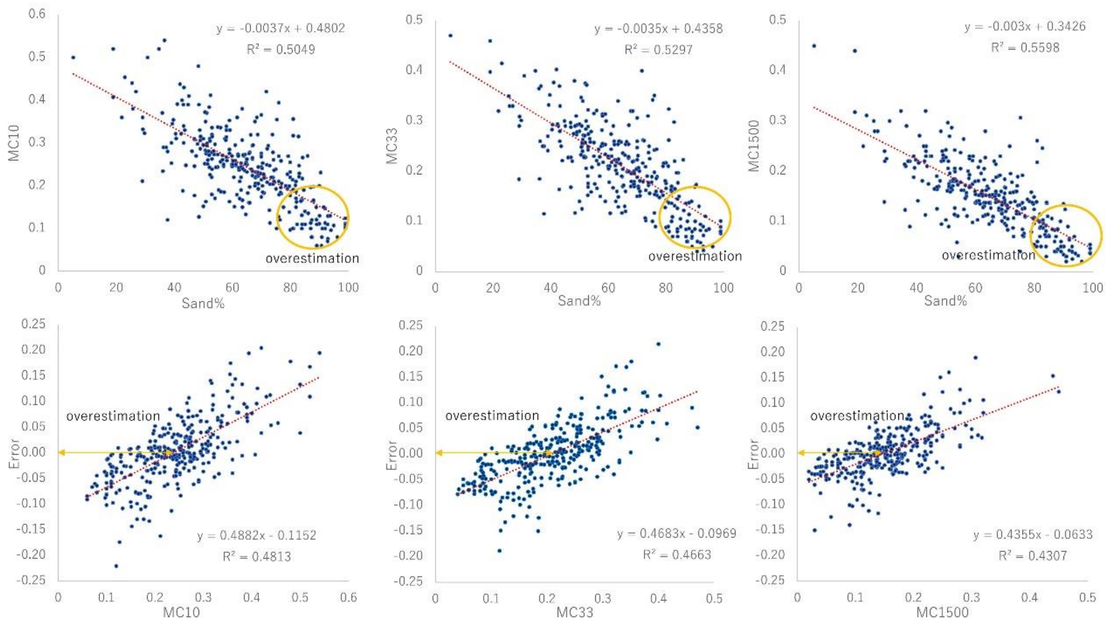

Figure 6.7. Relationship of error with sand percentage variation in PTFs developed using sand percentages

6.3.2. Model applications

The output of a PTF can serve as input to other functions when no measured data are available. It may increase or decrease the uncertainty of predictions depending on the level of error propagation and the sensitivity of inputs to the PTF outputs. Therefore, it is vital to study the functionality of PTFs for field-level applications. The primary application of soil hydrological parameters in agricultural soil is irrigation scheduling, which is an area of active research as water scarcity and irrigation costs increase.

Figure 6.8(a) shows that estimates of total available water in our Sri Lankan soil horizons made from measured and PTF-generated soil hydraulic properties were similar. Figure 6.8(b) shows the same close relationship for estimates of readily available water in the root zone above 75 cm depth, assuming a depletion level of 70%. Figure 6.9(a) shows a strong relationship between measurement-based and PTF-based estimates of the net irrigation requirement of maize at the six locations, and Figure 6.9(b) shows a strong relationship between measurement-based and PTF-based estimations for irrigation dates. Figure 6.10 shows that irrigation scheduling graphs based on measured and PTF-simulated soil hydraulic data for a maize crop in the Yala season at Hambantota were very similar. Irrigations in the PTF-based simulations were scheduled one day later during the middle of the crop growing season, and three days later near harvest time, but these differences may not affect the crop seriously as most crops are less sensitive to water stress during their late seasons. These results demonstrate that our newly developed PTFs function well in estimating irrigation water demand and scheduling irrigations of tropical Sri Lankan soils.

Very few studies have investigated the functionality of locally derived PTFs in field applications. Nemes et al. (2010) reported that well-tested PTFs could provide reasonable and reliable soil hydraulic data for scheduling irrigation. Functional evaluation of PTFs developed for Hungarian soils confirmed that estimated soil water contents agreed well with measurements (Nemes et al., 2003). In a study with temperate region soils (three locations) Soet and Stricker (2003) reported poor functional behavior of PTFs, but they used PTFs which had been developed elsewhere.

This study only considered the functionality of limited field-level applications. We suggest that further experiments be conducted to check the functionality of developed PTFs for more field-level applications, including process-based models, as such modeling efforts are severely hindered in Sri Lanka by the limited availability of soil hydraulic properties.

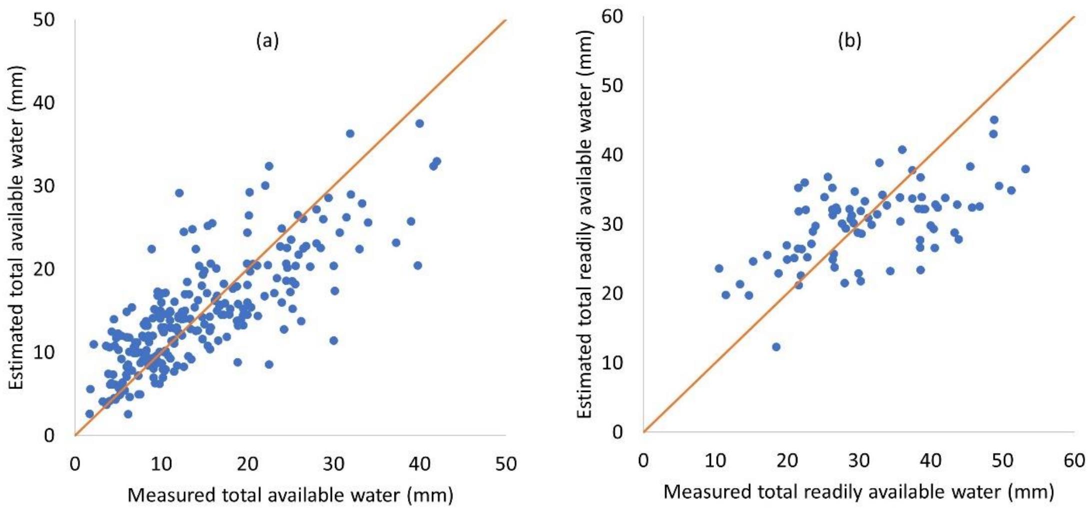

Figure 6.8. (a) Relationship between measurement-based and PTF estimation based total available water in separate soil horizons; (b) Relationship between measurement-based and PTF estimation based readily available water in the root zone (0-75 mm)

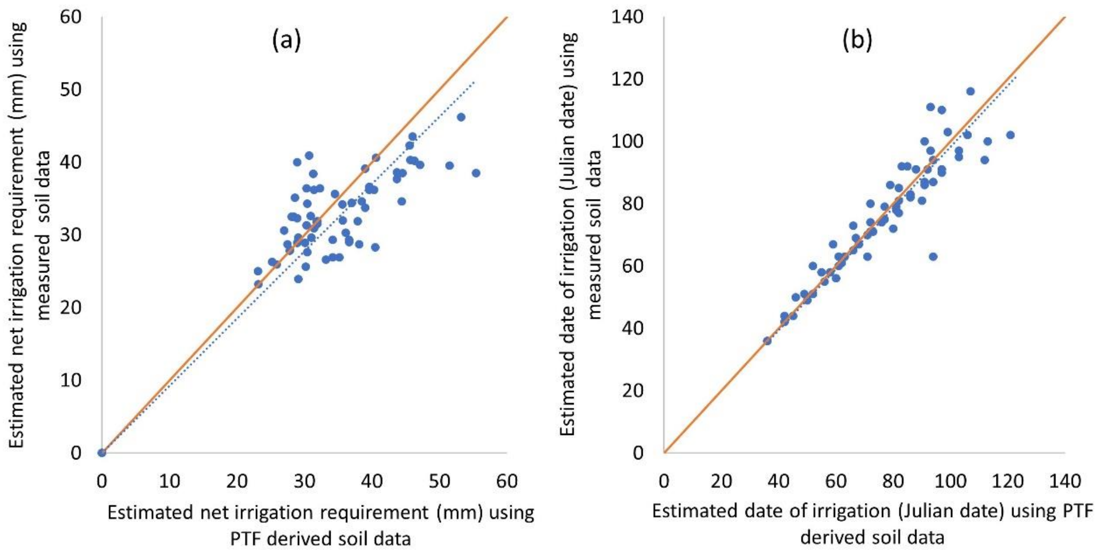

Figure 6.9. (a) Relationship between measurement-based and PTF estimation based net irrigation requirement of maize in selected locations in Sri Lanka; (b) Relationship between measurement-based and PTF estimation based maize irrigation dates (Julian dates) in selected locations in Sri Lanka

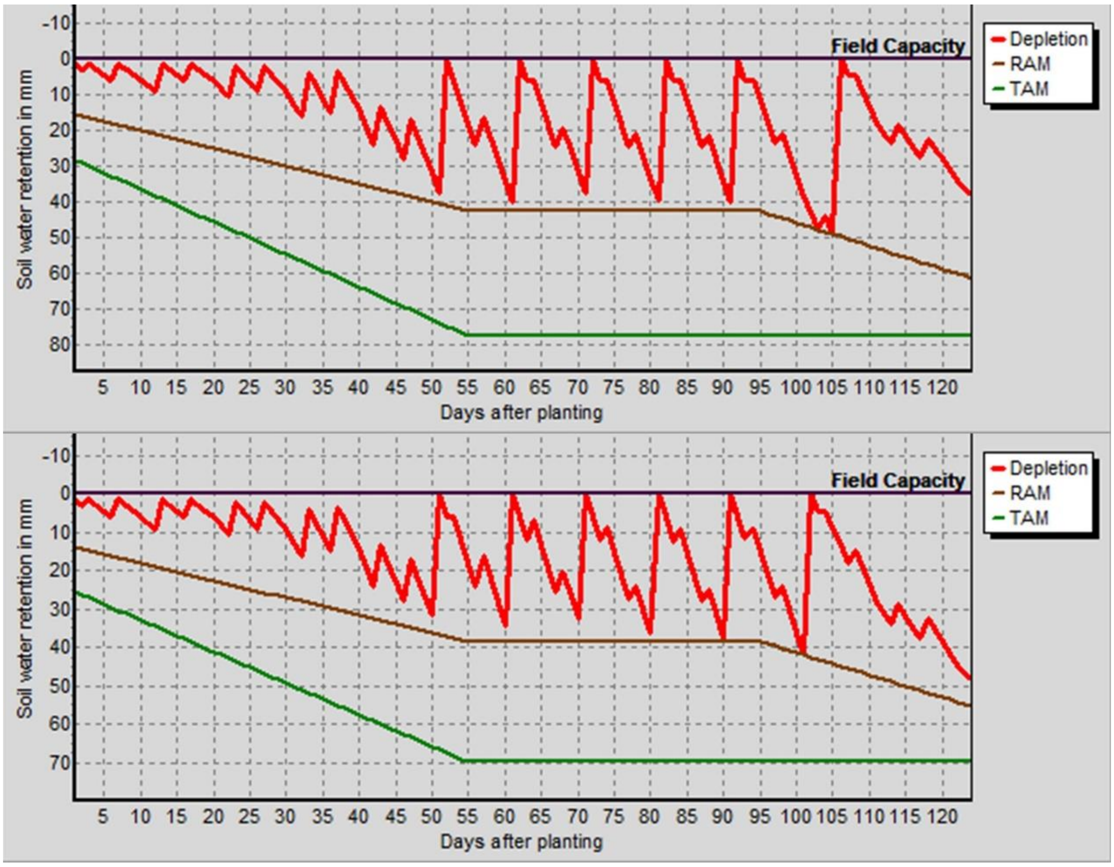

Figure 6.10. (a) Irrigation scheduling graph of maize crop in Yala season of Hambantota area estimated based on measured soil hydraulic data; (b) Irrigation scheduling graph of maize crop in Yala season of Hambantota area estimated based on PTF derived soil hydraulic data; Depletion – Level of soil moisture depletion of the root zone; RAM – Readily available moisture of the root zone; TAM – Total available moisture of the root zone

6.4. Conclusions

We were able to develop PTFs to estimate VWC of Sri Lankan soils at –10, –33, and –1500 kPa with reasonably good accuracy using sand content as the only input attribute (Table 6.3). Regardless of the climatic zone and soil type, these PTFs can be used anywhere in Sri Lanka without any modification. The addition of input values for silt and clay, bulk density, and organic carbon did not significantly improve the ability of PTFs to estimate VWC for Sri Lankan soils. It appears that PTFs developed from sand percentages are an easy and low-cost application that requires minimal equipment. However, it is advisable to use multiple inputs to minimize the possible risk of relying on the sand percentage as the sole input.

Our newly developed PTFs appear to be suitable for practical use in estimating irrigation water demand and scheduling irrigation for tropical Sri Lankan soils.

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7.0 Assessing the Applicability of OPSIS for Tropical Sri Lankan Conditions

7.1 Introduction

Sugarcane requires an evenly distributed water supply throughout its growing season to obtain the optimum yields. Thus, sugarcane under irrigation practices performs better, compared to the rain-fed conditions. Further, irrigation can ensure sustainability in crop production while in the meantime, increasing the flexibility of planting time and other field operations. Some authors reported that possible changes in climate might negatively influence on sugarcane growth and yield if no proper irrigation facilities are introduced (Carr and Knox, 2011; Carvalho et al., 2015; Santos and Sentelhas, 2012; Zhao and Li, 2015). Though sugarcane requires an abundant water supply; waterlogging conditions may create adverse effects on plant growth and yield (Skocaj et al., 2013). Therefore, appropriate drainage facilities also have to be provided as an essential part of water management in sugarcane fields. Due to the scarcity of freshwater and the competition from other water uses, dimensions of sugarcane irrigation have to be changed aiming to use water more efficiently and effectively. In this regard, it is essential to minimize significant losses such as evaporation, surface runoff, etc., to economize the limited available water.

Optimized subsurface irrigation system (OPSIS) is a newly developed subsurface irrigation system to irrigate upland crops. It is now commercially available in Okinawa, Japan and used to irrigate sugarcane crops. It can act as a drainage system too. Since water flows through gravity and only a small solar-powered pump uses to lift water to a higher elevation, OPSIS could be considered as a solution for the energy crisis in the world (Gunarathna et al., 2017). Solar-powered pump and minimum operational activities help to cut down operational costs of irrigation drastically, therefore, high potential to popular the OPSIS among the farmers where the operational costs are high. Using field experiments conducted in Itoman, Okinawa during 2013 to 2016, Gunarathna et al. (2018) reported the advantages of OPSIS over sprinkler irrigation for sugarcane cultivation in Okinawa in respect of both sugarcane yield and WUE. However, they suggested conducting further validation of results for different climatic conditions. Though the OPSIS is commercially available for sugarcane farmers in Okinawa, Japan, it may require further assessment /development before introducing to the other farming systems and environments.

Well calibrated and validated agricultural systems models is a fast-alternative option for developing and evaluating agronomic practices (Saseendran et al., 2008). It can extrapolate the results of site-specific conditions conducted for a limited number of seasons to other management and environmental conditions and a longer period (Balwinder-Singh et al., 2016). Hence crop models can act as a time and resource-saving option for researches on technological advances in agriculture. The results of such a study can be used to identify the possible management options for respective environmental conditions. Various crop models have been used for a range of applications including quantitative evaluation of climatic variability on yield (Pathak and Wassmann, 2009); analyzing productivity responses to climatic, irrigation fertilizer regimes (Arora et al., 2007); transplanting dates and irrigation schedules on yield and water productivity (Sena et al., 2014); determine the optimum allocation of limited irrigation between vegetative and reproductive growth stages and optimum soil water depletion level for initiating limited irrigation (Saseendran et al., 2008); determine the optimum irrigation depth (Abd-El-Baki et al., 2017); optimum soil moisture depletion and replenishment levels and timing and amount of irrigation during different crop growth stages (Kundu et al., 1982); optimize the irrigation conditions (Mubeen et al., 2016). However, no such evidence about the assessment of irrigation methods using a crop model.

APSIM (Agricultural Production Systems Simulator) is an open-source (for non-commercial users) crop modeling software, which can use to model growth and yield of many crops including sugarcane (Holzworth et al., 2014; Keating et al., 2003). Further, it has modeling functions, which allows simulating soil water, nutrients and many more (Holzworth et al., 2014; Inman-Bamber et al., 2016; Inman-Bamber and McGlinchey, 2003; Keating et al., 2003). APSIM allows users to incorporate management interventions by own scripts written in scripting languages. Hence, it is a significant advantage in APSIM compared to other crop modeling software (Archontoulis et al., 2014; Holzworth et al., 2014). The uncertainties of predictions from this model are generally characterized by the error statistics determined from the prediction of experimental data. Therefore, firm parameterization, calibration, and validation are needed to reduce the uncertainties of predictions.

Agriculture is one of the most sensitive sectors to the climatic change in terms of economy and social structure (Godfray et al., 2010). Process-based crop models driven by simulated future weather conditions are commonly used to study and quantify the impacts of climate change on agriculture. (Corbeels et al., 2018; Teixeira et al., 2018; Xiao et al., 2018). Global climate models (GCMs) provide possible future climates at regional and continental levels. However, it requires at a local scale for better decision making (Fowler et al., 2007). Coupled Model Intercomparison Project Phase 5 (CMIP5) listed numerous climate change scenarios developed by various modeling centers (Corbeels et al., 2018; McDermid et al., 2016; Xiao et al., 2018; Zubair et al., 2015). Different downscaling techniques use to generate future climatic conditions at local levels (Fowler et al., 2007). AgMIP Climate Scenario Generation Tools with R Version 2.3 is a tool developed by Agricultural model intercomparison project (AgMIP) to generate site-specific climates using 20 GCMs with four representative concentration pathways (RCPs) using CMIP5 GCM delta scenario approach (AgMIP, 2013; McDermid et al., 2016). The technique produces future climate scenarios by adjusting the historical observations of a given site according to the changes in precipitation, minimum and maximum temperatures based on predicted absolute changes in temperatures and relative changes in precipitation (Ruane et al., 2013). It uses bias-corrected statistical downscaling (BCSD) as a default method of downscaling (AgMIP, 2013).

This study aimed to assess the suitability of OPSIS for sugarcane farming in tropical Sri Lanka. We parameterized and calibrated the APSIM-Sugar model to simulate growth and yield of sugarcane local cultivar SL96128 using data obtained from field trials. Then, we simulated the growth and yield of sugarcane under rainfed, surface irrigated conditions and OPSIS irrigated conditions to compare the performances of those water regimes to assess the suitability of OPSIS to Sri Lankan conditions under present and future climatic conditions.

7.2 Materials and Methods

7.2.1 Parameterization and Calibration of APSIM-Sugar model

We collected necessary data from ongoing field trials of Gal-Oya Plantations (Pvt.) Ltd. We selected two farmer fields (farmer 1: 7° 13' 49" N, 81° 45' 52" E; farmer 2: 7° 15' 21" N, 81° 41' 38" E) located in Hingurana, Ampara, Sri Lanka for parameterization and calibration of APSIM-sugar model for locally grown cultivar SL96128. According to the Köppen climate classification, the southern dry zone of Sri Lanka is classified as As (tropical climate with a dry summer period) (Buysse, 2002).

7.2.1.1 Plant Data

We collected the growth and yield data of two farmer fields in Hingurana, Sri Lanka for parameterization and calibration of APSIM-Sugar model. The farmer field one was established in June 2013 and continued up to three ratoon crops. Crop duration was 375 days for the main crop and 365 days for ratoon crops. The farmer field two was established in June 2014 and continued up to two ratoons. Crop duration of the main crop and ratoon crops were maintained as 375 days and 300 days, respectively. Following the fertilizer recommendation for rainfed sugarcane, 225 kg/ha, and 250 kg/ha of urea were used in both fields. Randomly selected a 10 m^2 area was used to estimate the fresh cane yield of the crops.

7.2.1.2 Soil Data

Required soil data for the APSIM simulation were derived using PTFs developed by Gunarathna et al. (2019b) and other required data were gathered from SRICANSOL report (Dassanayake et al., 2010). The original soil profile was modified to make six layers to work with OPSIS module (Table 7.1).

Table 7.1. Soil data used to parameterize Hingurana soil profile

Depth (cm)	Bulk Density (g/cc)	Air Dry (mm/mm)	LL15 (mm/mm)	DUL (mm/mm)	SAT (mm/mm)	KS (mm/day)	Sugar LL (mm/mm)
0-10	1.450	0.062	0.124	0.183	0.440	1032	0.124
10-20	1.475	0.066	0.131	0.185	0.435	912	0.131
20-30	1.500	0.069	0.138	0.187	0.430	792	0.138
30-40	1.500	0.069	0.138	0.187	0.430	792	0.138
40-50	1.500	0.069	0.138	0.187	0.430	600	0.138
50-60	1.500	0.069	0.138	0.187	0.430	60	0.138

7.2.1.3 Climatological data

Daily meteorological data of Maduraketiya meteorological station (6° 50' 9" N, 81° 21' 36" E) were obtained from the meteorological department of Sri Lanka. Daily rainfall, maximum temperature, minimum temperature, and sunshine hours were obtained from 1997 to 2017. Sunshine hours were converted to solar radiation using the WeatherMan tool of DSSAT 4.6. Annual average ambient temperature and annual amplitude in mean monthly temperature were calculated using tav_amp utility software of APSIM (https://www.apsim.info/Products/Utilities.aspx).

7.2.1.4 APSIM Simulation

APSIM, the Agricultural Production Systems sIMulator is a process-based dynamic crop model that combines biophysical and management modules within a central engine to simulate diverse cropping systems (Holzworth et al., 2014; Keating et al., 2003). The model is driven by daily climate data and can simulate growth, development, and yield of crops and their interactions with soil.

First, we modified the sugar model of APSIM 7.10 by adding new cultivar SL96128. Then we parameterize the cultivar parameters using the data obtained from field measurements, published reports on SL96128 cultivar, and experts' views (Table 7.2). As APSIM underestimated the growth and yield, we modified the radiation use efficiency (RUE) like-minded Gunarathna et al. (2019a) and Sexton et al. (2017). We increased the maximum RUE values up to 2.0 confining the findings of De Silva and De Costa (2012) and Muchow et al. (1997). Similarly, we increased the maximum RUE values of ratoon crop up to 1.85 conforming the gap maintained by APSIM. As Sri Lankan sugarcane cultivars not tall like the listed cultivars in APSIM, we limited the maximum plant height up to 4000 mm from the default of 6000 mm. Further, we calibrated cane fraction (CF) and thermal time to emergence to the beginning of cane (EB) by trial and error method to find the optimum values for those parameters (Table 7.2).

Table 7.2. Cultivar and plant-specific parameters used to parametrization and calibration of APSIM-Sugar model

Parameter	Initial values (parameterization)		Values used for simulations (after calibration)	
	Crop	Ratoon	Crop	Ratoon
Leaf_size 1, 9, 20	3000, 50000, 50000	3000, 50000, 50000	3000, 50000, 50000	3000, 50000, 50000
cane_fraction	0.7	0.7	0.65	0.65
Sucrose_fraction_stalk 0.2, 1	1.0, 0.55	1.0, 0.55	1.0, 0.55	1.0, 0.55
sucrose_delay	0	0	0	0
min_sstem_sucrose	900	900	900	900
min_sstem_sucrose_redn	10	10	10	10
tt_emerg_to_begcane	1800	1800	1900	1900
tt_begcane_to_flowering	6000	6000	6000	6000
tt_flowering_to_crop_end	2000	2000	2000	2000
green_leaf_no	10	10	10	10
tillerf_leaf_size 1, 4, 10, 16	1, 1.5, 1.5, 1	1, 1.5, 1.5, 1	1, 1.5, 1.5, 1	1, 1.5, 1.5, 1
rue	0, 0, 1.80, 1.80, 1.80, 0	0, 0, 1.65, 1.65, 1.65, 0	0, 0, 2.05, 2.05, 2.05, 0	0, 0, 1.90, 1.90, 1.90, 0
Crop_height_max	6000	6000	4000	4000

As this study compares three water regimes, the same modified soil profile was used for all simulations.

7.2.2 Comparison of irrigation methods

We simulated the growth and yield of sugarcane under three water regimes as, rainfed, surface irrigated, and OPSIS irrigated conditions to assess the suitability of OPSIS for tropical Sri Lankan conditions. We selected two locations (Sevanagala in Monaragala district; 6° 22' 13" N, 80° 54' 47" E, and Hingurana in Ampara district; 7° 13' 49" N, 81° 45' 52" E) with two distinct soils (Table 7.3) to compare the growth and yield performances of sugarcane under rainfed, surface irrigated and OPSIS irrigated conditions. We simulated fresh cane yield, total above-ground biomass, and sucrose yield of local sugarcane cultivar SL96128 under three different water regimes.

Table 7.3. Basic Characteristics of soils in selected locations

Location	**Hingurana**	**Sevanagala**
Soil classification	Alluvial soils	Solodized Solonetz
Soil type	Loamy sand	Clay loam
Drainage class	Moderate well drained	Poorly drained
Average sand: silt: clay ratio of topsoil	85: 9: 5	41: 37: 22
Average sand: silt: clay ratio of subsoil	82: 9: 9	63: 15: 22

(Dassanayake et al., 2010)

7.2.2.1 Soil data

Required soil data for the comparison of three water regimes were derived using PTFs developed by Gunarathna et al. (2019b) and other required data were gathered from SRICANSOL report (Dassanayake et al., 2010). Two soil files for Hingurana and Sevanagala were prepared using those data. Original soil profiles were modified to make six layers to work with OPSIS (Table 7.1 and 7.4). As this study compares three water regimes, the same modified soil profiles were used for all simulations in the respective location.

Table 7.4. Soil data used to parameterize Sevanagala soil profile

Depth (cm)	Bulk Density (g/cc)	Air Dry (mm/mm)	LL15 (mm/mm)	DUL (mm/mm)	SAT (mm/mm)	KS (mm/day)	Sugar LL (mm/mm)
0-10	1.190	0.136	0.271	0.377	0.551	65.040	0.271
10-20	1.190	0.136	0.271	0.377	0.551	65.040	0.271
20-30	1.410	0.144	0.287	0.375	0.468	68.880	0.287
30-40	1.410	0.144	0.287	0.375	0.468	68.880	0.287
40-50	1.410	0.144	0.287	0.375	0.468	68.880	0.287
50-60	1.410	0.144	0.287	0.375	0.468	68.880	0.287

7.2.2.2 Meteorological data

Daily meteorological data of two selected locations were extracted from AgMERRA global gridded climate dataset using NetCDF-Extractor V2.0 tool of AgriMetSoft (https://www.agrimetsoft.com). Daily rainfall, maximum temperature, minimum temperature, and solar radiation obtained from 1980 to 2010. Annual average ambient temperature and annual amplitude in mean monthly temperature were calculated using tav_amp utility software of APSIM (https://www.apsim.info/Products/Utilities.aspx).

7.2.2.3 APSIM simulation

We simulated the growth and yield of sugarcane from 1980 - 2010 for two locations. In all simulations, we maintained 375 days and 365 days respectively for main and ratoon crops. We simulated the growth and yield of sugarcane of six cropping cycles as one cycle includes the main crop and four ratoon crops. In surface irrigation simulations, irrigation was scheduled in 14 days interval if the rainfall did not exceed 25 mm within last three days, else postponed for ten days. The amount per irrigation was set as 60 mm of irrigation with a maximum of 600 mm per season. We used the APSIM-OPSIS module to couple optimized subsurface irrigation system to the APSIM engine in APSIM simulations under OPSIS irrigated conditions. The fifth layer was selected as the base layer, where the layer we propose to locate OPSIS. The difference between the SAT and the soil water content (SW) of the layer is identified as the input to the layer. It is the estimated amount of irrigation through the optimized subsurface irrigation and named as "opsis (mm/day)". We used 350 kg/ha and 375 kg/ha of urea fertilizer for main and ratoon crops, respectively in all simulations.

7.2.3 Performance of OPSIS in changing Climate

We simulated the growth and yield of sugarcane under rainfed, surface irrigated, and OPSIS irrigated conditions with simulated future climates to assess the suitability of OPSIS for tropical Sri Lankan conditions in possible future climates. We selected Sevanagala in Monaragala district; 6° 22' 13" N, 80° 54' 47" E for this simulation. We simulated fresh cane yield, total above-ground biomass, and sucrose yield of local sugarcane cultivar SL96128.

7.2.3.1 Meteorological data

We simulated future climate scenarios considering the baseline period of 1980 – 2010. We generated site-specific future climates of near-future period (2020 - 2039) using

AgMIP Climate Scenario Generation Tools with R Version 2.3 for 20 GCMs and two representative pathways (RCPs) 4.5 and 8.5. Then AgMIP files of future climate scenarios were converted to APSIM format using QUADUI tool of AgMIP.

7.2.3.2 APSIM simulation for future climates

We simulated the growth and yield of sugarcane for the near future (2020 – 2039) using the simulated climate files. All simulation conditions were kept similar to section 7.2.2.3. We neglected the crop response CO_2 as CO_2 fertilization has limited effect on photosynthesis of C4 plants (Corbeels et al., 2018) and APSIM's poor ability to capture the secondary effect of reducing crop transpiration (Durand et al., 2018).

7.2.4 Statistical analysis

We assessed the simulation accuracy of the calibrated model using root mean square error (RMSE; Equation 7.1), mean absolute error (MAE; Equation 7.2), coefficient of determination (R^2; Equation 7.3) and Wilmott's agreement index (d; Equation 7.4) (Dias and Sentelhas, 2017; Krause et al., 2005; Willmott, 1981). Low RMSE, MAE values, and high R^2, d values indicate good agreement between model outputs and observed values.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{\mathrm{i}=1}^{\mathrm{n}}(\mathrm{S_i} - \mathrm{O_i})^2} \tag{7.1}$$

$$MAE = \frac{1}{n}\sum_{\mathrm{i}=1}^{\mathrm{n}}|\mathrm{S_i} - \mathrm{O_i}| \tag{7.2}$$

$$R^2 = \left[\frac{\sum_{i=1}^{n}(O_i-\bar{O})(S_i-\bar{S})}{\sqrt{\sum_{i=1}^{n}(O_i-\bar{O})^2}\sqrt{\sum_{i=1}^{n}(S_i-\bar{S})^2}}\right]^2 \tag{7.3}$$

$$d = 1 - \frac{\sum_{i=1}^{n}(S_i-O_i)^2}{\sum_{i=1}^{n}(|S_i-\bar{O}|+|O_i-\bar{O}|)^2} \tag{7.4}$$

Where, S_i and O_i are the simulated and observed value of the parameter (in fresh cane yield (t/ha), plant height (mm), soil moisture (mm/mm) irrigation water (mm/month) respectively; $\bar{O}$ and $\bar{S}$ are the average of simulated and observed values respectively; and n is the number of observations.

We compared the effect of irrigation method over 40 different climatic conditions (derived using 20 GCMs and two RCPs) using analysis of variance (ANOVA) procedures in R software (R Core Team, 2018). We did pairwise comparisons using Turkey's HSD test at $P<0.05$.

7.3 Results and Discussion

7.3.1 Parameterization and calibration of APSIM-Sugar to simulate growth and yield of cultivar SL96128

Initially, we added cultivar SL96128 to the APSIM-Sugar model (XML file) and parameterized using field measured data (leaf size and green leaf number), available data in published reports, and views of experts (Table 7.2). After parameterization, we simulated fresh cane weight and observed quite healthy relationships between observed and simulated values. However, APSIM underestimated the fresh cane weight. After the modification of plant parameters (maximum RUE and maximum plant height of main and ratoon crops) and calibration of cultivar parameters (CF and EB), the relationships were further improved (Figure 7.1). Despite of the high variability of cane yield and sucrose affected by weather conditions, nutrient levels, planting time and some undefined factors, APSIM sugarcane able to simulate good results to fit with the observations in agreement with the results of Keating et al. (1999), Cheeroo-Nayamuth et al. (2000) and Inman-Bamber and McGlinchey (2003). Using data sets of different cultivars grown in different locations, Keating et al. (1999) showed that APSIM could simulate the millable stalk weight (R^2= 0.72, RMSD = 1.94 t/ha) with fairly good accuracy. Our study also proves the virtuous ability of APSIM to simulate fresh cane weight as all model evaluation criteria shows good fit between simulations and observations (RMSE = 7.82 t/ha, MAE = 6.47 t/ha, R^2 = 0.85, d = 0.95).

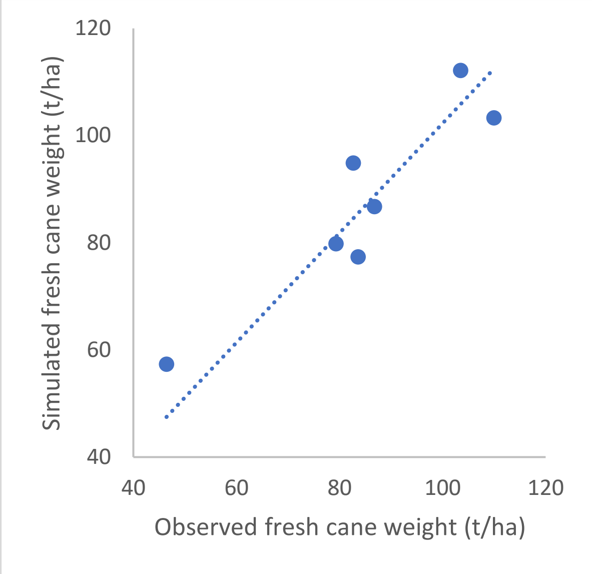

Figure 7.1. Observed versus simulated fresh cane weight of sugarcane cultivar SL96128

7.3.2 Performance of OPSIS compared to rainfed and surface irrigation method

We simulated the fresh cane weight, total above-ground biomass and sucrose weight of sugarcane cultivar SL96128 under rainfed, surface irrigated and OPSIS irrigated conditions for two sugar-growing locations of Sri Lanka. Results revealed that OPSIS performed well compared to both rainfed and surface irrigated conditions.

7.3.2.1 Above-ground biomass

Results revealed that there are significant differences in aboveground biomass between irrigation methods and locations. OPSIS showed significantly higher above-ground biomass (5792 g/m^2) compared to the surface irrigation (5371 g/m^2) and rainfed conditions (4748 g/m^2). Surface irrigation also reported significantly higher above-ground biomass than the rainfed conditions. Sevenagala (clay loam soil) reported higher above-ground biomass (5707 g/m^2) compared to the Hingurana (loamy sand soil) (4900 g/m^2). Figure 7.2 shows the box plot diagram of simulated biomass of three different water regimes for two locations. In Sevanagala, all three water regimes showed distinct variation among them as OPSIS showed significantly higher above-ground biomass (6191 g/m^2) compared to rainfed conditions (5275 g/m^2) and surface irrigated conditions (5655 g/m^2). Surface irrigation also showed notable performances over rainfed conditions. Under the loamy sand soil conditions (Hingurana) also, OPSIS showed significantly higher above-ground biomass (5394 g/m^2) compared to rainfed (4221 g/m^2) and surface irrigation (5086 g/m^2). Similar to the Sevanagala, surface irrigation also showed notable performances over rainfed conditions.

With clay loam soil (Hingurana), all three methods showed poor performances compared to clay loam soil (Sevanagala).

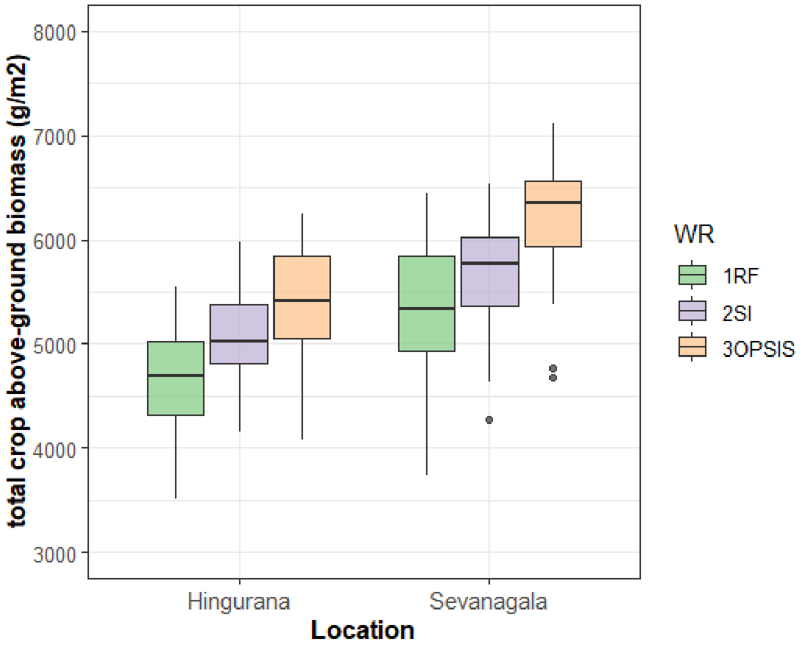

Figure 7.2. Simulated total above-ground crop biomass under rainfed, surface irrigated and OPSIS irrigated conditions

7.3.2.2 Fresh cane weight

There are significant differences of fresh cane yield between irrigation methods and locations. OPSIS showed significantly higher cane fresh weight (137.42 t/ha) compared to the surface irrigation (128.32 t/ha) and rainfed conditions (112.62 t/ha). Surface irrigation also reported significantly higher cane fresh weight than the rainfed conditions. Sevenagala (clay loam soil) reported higher cane fresh weight (135.15 t/ha) compared to the Hingurana (loamy sand soil) (117.09 t/ha). Figure 7.3 shows the box plot diagram of simulated fresh cane yield of three different water regimes for two locations. In Sevanagala, all three water regimes showed distinct variation among them as OPSIS showed significantly higher fresh cane yield (145.94 t/ha) compared to rainfed conditions (124.85 t/ha) and surface irrigated conditions (134.66 t/ha). Surface irrigation also showed significant performances over rainfed conditions. Under the loamy sand soil conditions (Hingurana) also, OPSIS showed significantly higher cane fresh weight (128.90 t/ha) compared to rainfed (100.38 t/ha) and surface irrigation (121.97 t/ha). With clay loam soil, all three methods showed poor performances compared to clay loam soil.

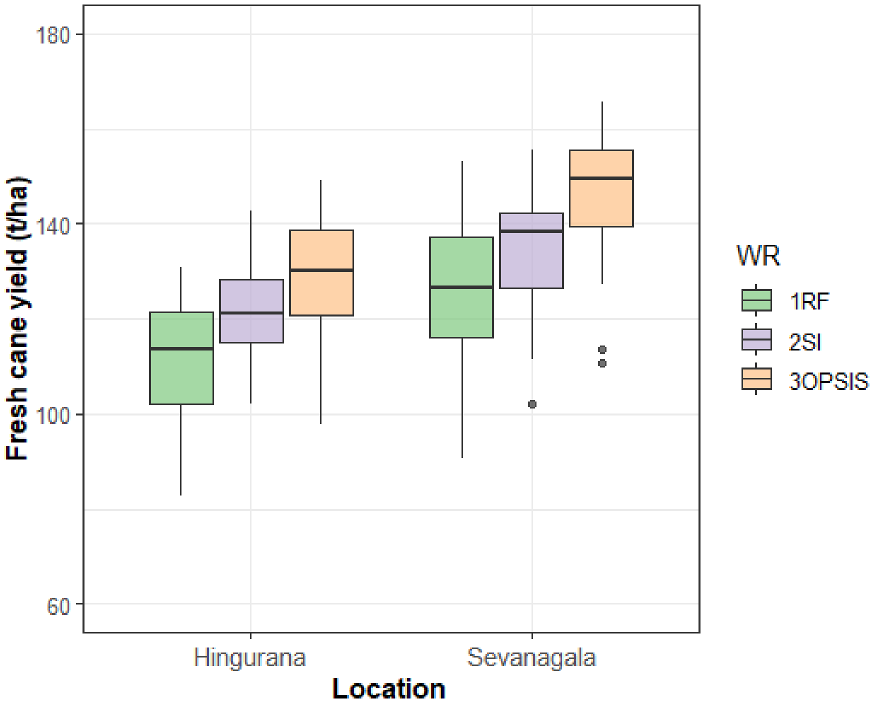

Figure 7.3. Simulated fresh cane yield under rainfed, surface irrigated and OPSIS irrigated conditions

7.3.2.3 Sucrose yield

OPSIS showed significantly higher sucrose yield (2361 g/m^2) compared to the surface irrigation (2192 g/m^2) and rainfed conditions (1861 g/m^2). Surface irrigation also reported significantly higher sucrose yield than the rainfed conditions. Sevenagala (clay loam soil) reported significantly higher sucrose yield (2237 g/m^2) compared to the Hingurana (loamy sand soil) (2039 g/m^2). Figure 7.4 shows the box plot diagram of simulated sucrose yield of three different water regimes for two locations. In Sevanagala, all three water regimes showed distinct variation among them as OPSIS showed significantly higher sucrose yield (2443 g/m^2) compared to rainfed conditions (2005 g/m^2) and surface irrigated conditions (2263 g/m^2). Surface irrigation also showed significant performances over rainfed conditions. Under the loamy sand soil conditions (Hingurana) also, OPSIS showed significantly higher sucrose yield (2279 g/m^2) compared to rainfed (1718 g/m^2) and surface irrigation (2120 g/m^2). With clay loam soil, all three methods showed poor performances compared to clay loam soil.

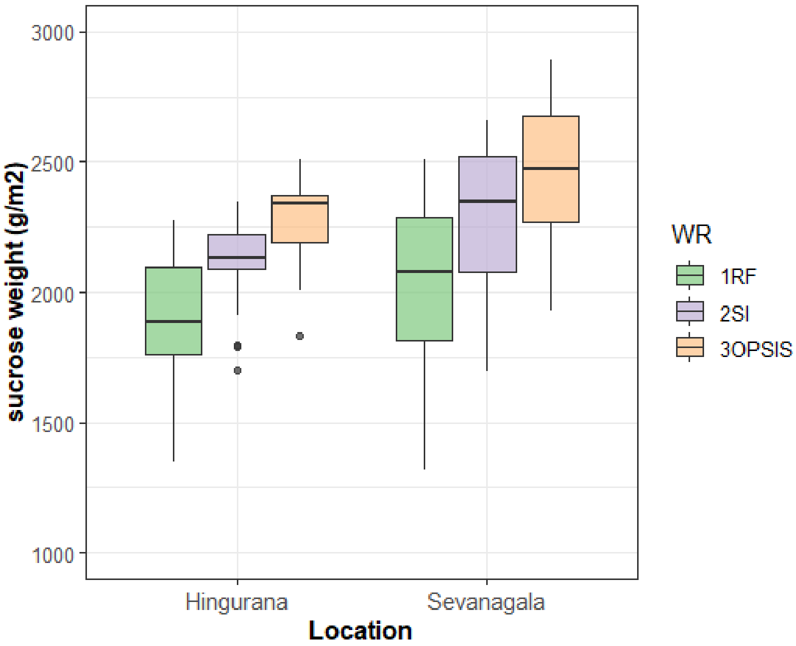

Figure 7.4. Simulated sucrose weight under rainfed, surface irrigated and OPSIS irrigated conditions

Clay loam soil in Sevanagala shows relatively higher water holding capacity compared the Hingurana soil. Hence, Sevanagala gives higher yield under the rainfed conditions due to less moisture stress. The yield of sugarcane in the Sevanagala area has further increased with the addition of surface irrigation. The allocated limit of 600 mm is enough to irrigate the entire growing season; hence, no moisture stress during the growing season. Application of OPSIS further enhanced the yield of sugarcane in the Sevanagala area as OPSIS provides minimum water stress to crop as well as the better nutrient availability due to the split application of fertilizer. Poor water holding capacity of Hingurana soil compared to the Sevanagala soil leads to poor performances of rainfed conditions and both irrigation methods. Under the rainfed conditions, utilization of rainfall is limited in Hingurana soil compared to the high water-holding Sevanagala clay loam soils. Under the surface irrigation, Hingurana soil uses frequent irrigation, hence quickly finish the allocated amount compared to the Sevanagala soils, then crop faces moisture stress during the mid-season of the crop. In OPSIS, the upper layers of the root zone receive water through the capillarity. Since capillary rise is poor in coarse-textured soils, top layers of Hingurana soil profile remained dry in most of the times, hence poor growth and yield performances with OPSIS. Similar kind of yield variation in Sevanagala and Hingurana was observed and reported by Keerthipala and Dharmawardene, (2000). They observed 142 t/ha and 102 t/ha of fresh cane yield in Sevanagala and Hingurana, respectively under irrigated conditions. In a study conducted in Udawalawa, Sri Lanka (Near to Sevanagala), Silva and Costa, (2004) reported average fresh cane yield of 140 (±23.5) t/ha and 91(±19.8) t/ha for irrigated and rainfed conditions respectively. In our simulations, we simulated higher fresh cane yield (125 t/ha) under rainfed conditions in Sevanagala than they reported. The difference may attribute to the difference of fertilizer levels, as we used higher fertilizer levels considering the updated fertilizer recommendations for irrigated sugarcane with higher yields.

OPSIS gives optimum soil moisture conditions and available nutrient conditions for crop growth. However, as the moisture condition in top layers is critical than lower layers of sugarcane crop, OPSIS may not perform well in sandy soils compared to the clay soils. Therefore, the usual establishment configuration may have to change when introducing OPSIS to the other soil/climate conditions. In Okinawa, Japan, where the OPSIS introduced, OPSIS usually laid out 45 cm below the ground level to irrigate sugarcane. Installation of OPSIS under 45 cm below the ground level performed well with Sevanagala soils but not with Hingurana soils. However, it can be varied between 30 - 60 cm based on the soil type and crop grown (Gunarathna et al., 2017). Therefore, a comprehensive assessment of OPSIS design should be required when introducing to other environments.

7.3.3 Performance of OPSIS in future climates

We used APSIM 7.10 crop model with the calibrated APSIM-Sugar model for local cultivar SL96128 to assess the performances of different water regimes (rainfed, surface irrigation and OPSIS) in possible future climates of Sevanagala, Sri Lanka. We simulated the fresh cane yield, crop above-ground biomass and sucrose yield of sugarcane using projected future climates (2020 – 2039) under 20 GCMs and two RCPs.

7.3.3.1 Crop growth and yield of sugarcane under future climates

Figure 7.5 shows the box plot diagram of the simulated crop above-ground biomass, fresh cane weight, and sucrose yield for the period of (2020 – 2039) using different GCMs and emission scenarios. It shows that all the selected growth and yield parameters of sugarcane varied widely based on GCMs and emission scenarios. Therefore, we used an ensemble of simulations with different GCMs to compare the performances of different water regimes on selected outputs. Figure 7.6 shows the performances of water regimes on selected outputs under two emission scenarios considered. Results revealed that OPSIS might show significantly higher above-ground biomass, fresh cane yield and sucrose yield compared to the surface irrigation and rainfed conditions in future climates (2020 – 2039) under both emission scenarios (Table 7.5). Surface irrigation also may show significantly higher above-ground biomass, fresh cane yield, and sucrose yield compared to the rainfed conditions in future climates under both emission scenarios. However, for all selected outputs, no significant difference was observed between two emission scenarios.

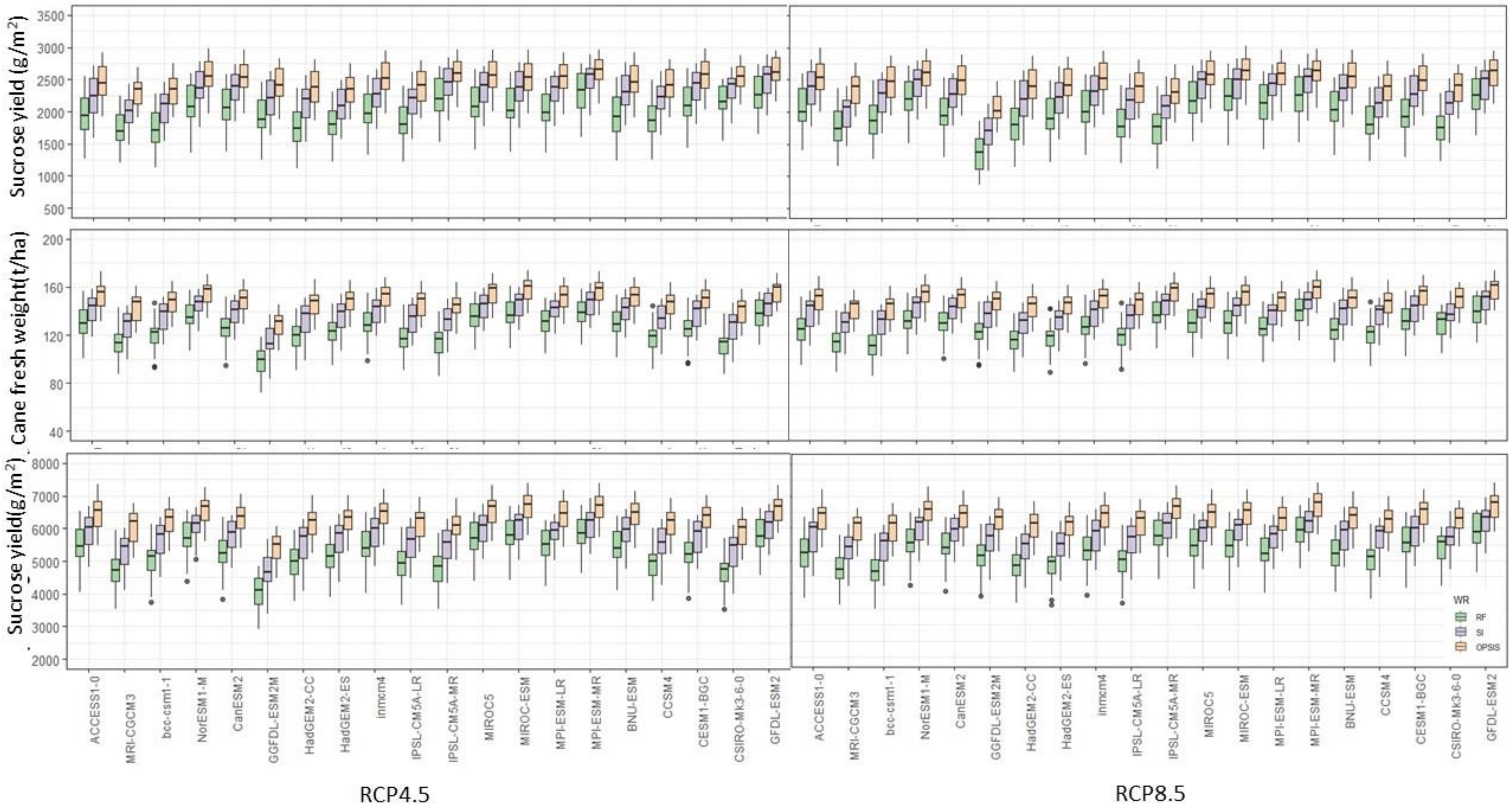

Figure 7.5. Boxplot diagrams of simulated future (2020- 2039) sucrose weight, fresh cane weight and above-ground biomass of sugarcane

Table 7.5. Performances of different water regimes under different emission scenarios: Ensemble results of simulated crop above-ground biomass, fresh cane weight, and sucrose weight for the near-future period (2020-2039)

Water regime	RCP4.5			RCP8.5		
	RF	SI	OPSIS	RF	SI	OPSIS
Biomass	5174[a]	5704[b]	6299[c]	5238[a]	5760[b]	6338[c]
Cane fresh weight	123.62[p]	136.83[q]	149.39[r]	125.26[p]	138.26[q]	150.43[r]
Sucrose weight	1954[x]	2235[y]	2468[z]	1992[x]	2271[y]	2486[z]

Row means followed by the same letter are not significantly different at 5% level of significance using Tukey's HSD

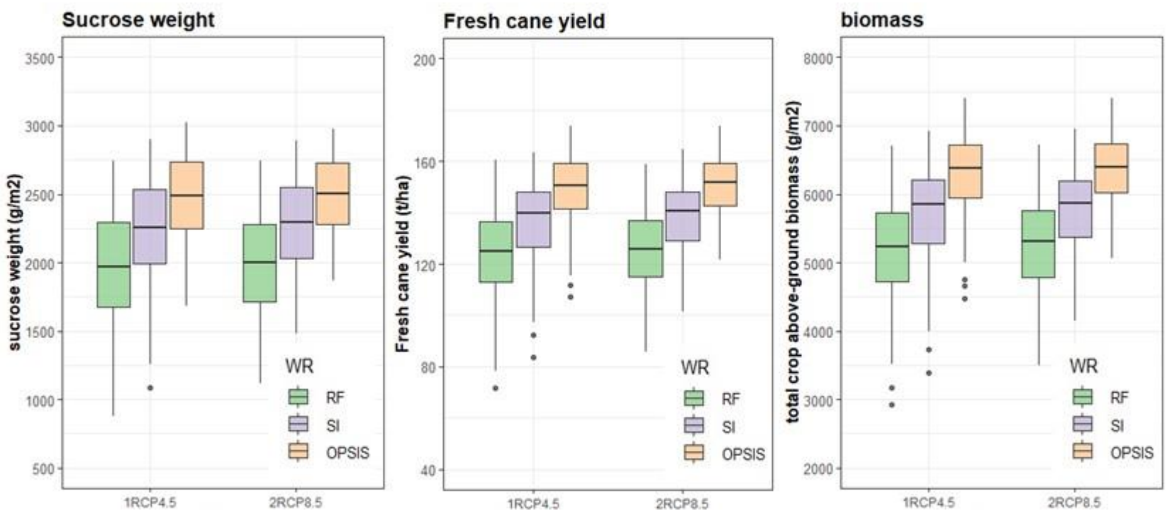

Figure 7.6. Performance of different water regimes in possible future climates: Ensemble of simulated growth and yield of sugarcane with different GCMs

Compared to the baseline period (1980-2010), according to both emission scenarios, surface irrigation, and OPSIS might slightly increase the crop above-ground biomass, fresh cane yield, and sucrose yield of sugarcane. Hence, we can convert the climate change impacts to a positive direction (in terms of crop yield) by assuring a proper irrigation method for sugarcane cultivation. We estimated that, the OPSIS will increase the fresh cane yield by 2.4% (-11.4% to 8.7%) under the RCP4.5 emission scenario and 3.1% (-2.5% to 9.0%) under the RCP8.5 emission scenario compared to the baseline period while surface irrigation remains 1.6% (-14.5% to 23.7%) and 2.7% (-4.2% to 10.5%) respectively for the same.

Rainfed conditions will decrease the fresh cane yield by 1% (-21% to 10.4%) and increase 0.3% (-10.5% to 12.2%) for RCP4.5 and RCP8.5 emission scenarios respectively. Further, results showed a higher uncertainty of rainfed conditions followed by surface irrigation, while the OPSIS showed the least.

7.4 Conclusions and Recommendations

We modified the APSIM-Sugar model to simulate growth and yield of Sri Lankan local sugarcane cultivar SL96128. Then we parameterize the cultivar SL96128 using measured values, information in published reports, and expert's views. However, APSIM underestimated the growth and yield of sugarcane cultivar SL96128. Therefore, the APSIM-Sugar model was modified and calibrated using radiation use efficiency, thermal time from emergence to the beginning of cane and cane fraction. After the calibration, APSIM simulations showed a close relationship with the observations.

Then we simulated the growth and yield of sugarcane under rainfed, surface irrigated and OPSIS irrigated conditions for two locations in Sri Lanka with a distinct variation of soil as clay loam and loamy sand soils. Results revealed that in both soils, OPSIS performed better than the rainfed and surface irrigation. However, the performance of OPSIS is remarkable with clay loam soil. Hence, we can conclude that OPSIS can significantly increase the crop growth and sugarcane under Sri Lankan conditions, especially in the places with clayey soils. The design modification may require to achieve expected performances of OPSIS under sandy soil conditions.

OPSIS can assure the higher yields compared to the surface irrigation and rainfed conditions even with the possible climate changes predicted using different GCMs and emission scenarios.

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8.0 General Conclusions

This study aimed to introduce the OPSIS and develop the capabilities of APSIM to simulate the growth and yield of sugarcane with OPSIS aiming future development of OPSIS in Japan and other parts of the world. A series of field experiments and simulations were conducted to achieve this goal, and we made the following conclusions.

The optimized subsurface irrigation system (OPSIS) is a subsurface irrigation system for irrigating the root zone of upland crops by capillarity. OPSIS shows improved water-saving capability compared with other irrigation methods as it can function with minimum percolation, evaporation, and surface runoff. Because a small solar-powered pump is used to lift water and create a pressure head and because minimum operational activities are required while ensuring a good yield. OPSIS can use on slopes where surface irrigation is not suitable. Hence, it requires less attention to land leveling than surface irrigation methods, and it is better than other irrigation methods in achieving equal distribution of irrigation water on slopes. Water-soluble fertilizers can effectively use with OPSIS. OPSIS can act as a subsurface drainage system. Therefore, crop fields may not require a separate drainage system for water management in fields which OPSIS installed.

Field experiments confirmed that OPSIS offers advantages over sprinkler irrigation for sugarcane cultivation in Okinawa in respect of both sugarcane yield and WUE. Compared with sprinkler irrigation, OPSIS produced significantly taller plants, and thus significantly longer millable stalks, and significantly more millable stalks. Therefore, OPSIS achieved significantly higher fresh cane weight using less irrigation water than the sprinkler irrigation. OPSIS is a water-conserving irrigation technique that can irrigate sugarcane crops with minimal operational cost, energy consumption, and human intervention. Therefore, it may be a sustainable alternative for sugarcane irrigation in Okinawa and similar subtropical environments.

The global sensitivity analysis conducted using Gaussian Emulator Machine for Sensitivity Analysis (GEM-SA) showed that green leaf number and cane fraction were ideal candidates for parameterization of cultivars in both Okinawan and Sri Lankan environments. The study found that thermal time from emergence to the beginning of cane, to minimum structural stem sucrose content (MSS), MSS reduction and sucrose fraction are the ideal parameters to calibrate assuring good growth and yield simulations of sugarcane using APSIM model. Further, the study concluded that, although they are not listed as cultivar parameters in APSIM-Sugar model, if reliable and ample data available, calibrate transpiration efficiency of growth stage four and radiation use efficiency of growth stages three and four also.

APSIM-Sugar model was parameterized and calibrated to simulate growth and yield of sugarcane cultivar Ni21 in Okinawan conditions. APSIM-OPSIS module was developed to couple OPSIS with APSIM engine. Then, the APSIM model was validated to use with OPSIS. Simulated plant height and fresh cane yield showed good agreement with the observations. However, APSIM showed overestimation for soil water content in upper soil layers and irrigation water use of OPSIS. Hence, newly developed APSIM-OPSIS module can successfully be used to simulate the crop growth and yield of sugarcane with optimized subsurface irrigation system.

Pedotransfer functions (PTFs) were developed to estimate the volumetric water content of Sri Lankan soils at –10, –33, and –1500 kPa with reasonably good accuracy using sand content as the only input attribute. Regardless of the climatic zone and soil type, these PTFs can be used anywhere in Sri Lanka without any modification. Newly developed PTFs are appeared to be suitable for practical use in estimating irrigation water demand, scheduling irrigation and crop modeling in tropical Sri Lankan conditions.

APSIM-Sugar model was parameterized and calibrated to simulate growth and yield of Sri Lankan local sugarcane cultivar SL96128. Then the growth and yield of sugarcane were simulated under rainfed, surface irrigated and OPSIS irrigated conditions for two locations in Sri Lanka with a distinct variation of soil as clay loam and loamy sand soils. Results revealed that in both soils, OPSIS performed better than the rainfed and surface irrigation; however, the performance of OPSIS is remarkable with clay loam soil. Hence, the study concluded that the OPSIS could significantly increase the crop growth and sugarcane under Sri Lankan conditions, especially in the places with clayey soils. The design modification may require to achieve expected performances of OPSIS under sandy soil conditions. OPSIS can assure the higher yields compared to the surface irrigation and rainfed conditions even with the possible climate changes predicted using different GCMs and emission scenarios.