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Optimizing Maize Yield under Subsurface Drip and Deficit Irrigation using Sowing Date and Temperature in CropSyst

Taofeek Samuel WAHAB[1] , Alkhan SARIYEV[2] , Mert ACAR[3] , Celaleddin BARUTÇULAR[4] , Ahmet ÇILEK[5]

[1,2,3]Department of Soil Science and Plant Nutrtion, Faculty of Agriculture, Çukurova University, Adana, Türkiye
[4]Department of Field Crops, Faculty of Agriculture, Çukurova University, Adana, Türkiye
[5]Department of Landscape Architecture, Faculty of Architecture, Çukurova University, Adana, Türkiye

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Corresponding Author
Taofeek Samuel Wahab
samtrek@yahoo.com

Author ORCID
[1]https://orcid.org/0000-0001-9192-5946
[2]https://orcid.org/0000-0003-2832-0113
[3]https://orcid.org/0000-0002-9971-4470
[4]https://orcid.org/0000-0003-3583-9191
[5]https://orcid.org/0000-0002-6781-2658

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Abstract

Optimizing agricultural output through modeling can aid in planning, reduce the environmental impacts of agricultural activities, and enhance yields under deficit agricultural inputs. Climatic and agronomic data were collected from three subsurface irrigation regimes (I100 irrigation to field capacity (FC), I75 irrigation to 75% FC and I50 irrigation to 50% FC) over three years (2017–2019) at Cukurova University Agricultural Experimental Station. The treatments were applied in a completely randomized block design with three replications. 2019 data was used for model calibration, and 2017 and 2018 data were used for validation. Optimization involved adjusting the sowing date backward and manipulating temperature levels. The Cropping Systems Simulation Model (CropSyst) was successfully calibrated, except for the I50 Leaf area index (LAI), having a low regression coefficient and high root mean square error, an indication that CropSyst may not accurately simulate LAI at low deficit irrigation (DI). Promising results were obtained through sowing date optimization, particularly with I50 exhibiting the greatest yield improvement. Altering the average atmospheric temperature by a few degrees did not negatively affect I100, while DI applications resulted in yield loss at temperatures higher than 30 °C. CropSyst could not estimate maize yield at extreme temperatures for all treatments (above 40 °C) during the anthesis stage, indicating that the model may not be sensitive to certain maize growth stages. The optimization results indicate that for DI regimes to be competitively adopted as an alternative strategy for irrigation water conservation, the appropriate sowing date or temperature range must be carefully considered.

Keywords: Calibration, Crop growth, Crop modeling, Simulation, Soil water management

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INTRODUCTION

Water availability is one of the most important factors affecting food security, and shortages of water may further worsen the situation (Tularam and Hassan, 2016; Karandish et al., 2021). Rapidly changing climatic conditions require the reversal of current irrigation strategies (Rocha et al., 2020). Deficit irrigation emerges as a key method for reducing irrigation water usage, making conservation of agricultural water use possible, addressing concerns regarding water shortage, scarcity and the environmental impact of agriculture. However, a significant challenge associated with deficit irrigation (DI) is the potential for yield loss (Comas et al., 2019). Timely and precise irrigation schedule management represents a potential solution to mitigate these challenges (Linker et al., 2018; Li et al., 2022; Mirhashemi, 2022), focusing on crucial crop growth stages, irrigation methods (Wu et al., 2018; Irmak et al., 2022), and planting dates (Williams et al., 2018; Getachew et al., 2021). While DI offers a pathway for conserving irrigation water, optimizing DI through agronomic practices, such adjusting sowing dates and monitoring atmospheric temperature, can reduce yield losses associated with high irrigation demand crops. In addition to adopting the DI strategy and optimizing sowing date and temperature ranges, subsurface drip irrigation (SDI) emerges as a practical means to minimize water loss inherit in alternative irrigation systems (Ayars et al., 2015; Wang et al., 2021). This is achieved in SDI by directly delivering water to plant roots (Wang et al., 2020), reducing surface runoff (Leng et al., 2017) and other losses associated with other forms of irrigation. The integration of these three strategies make effective conservation of irrigation water possible for crops with high irrigation requirement.

Irrigation water use is dependent on climatic, edaphic factors and management strategies. Temperature, as an environmental factor, plays a crucial role in limiting evapotranspiration in plants (Lu et al., 2005). Plants achieve optimum transpiration under unstressed conditions, and DI-induced stress reduces this optimal transpiration (Gonzalez-Dugo et al., 2018; Liao et al., 2022). However, under appropriate conditions, optimizing DI-induced stress can enhance water use efficiency and conserve irrigation water (van Donk et al., 2013; Zhang et al., 2021; Yadav et al., 2024). Identifying the right temperature range to maximize maize yield under DI applications is highly beneficial when adopting such a strategy. The sowing date is closely related to the optimum temperature for maize plants in DI applications. The sowing date is a management tool used in deciding the window period during which a particular crop is planted. Selecting the right sowing date ensures that plants grow under the right conditions for optimum yield (Mugiyo et al., 2021) and prevents or reduces plant exposure to stress-inducing external conditions, enabling plants to utilize the resources of the soil.

Estimating the appropriate date and temperature conditions for planting maize under DI conditions can be tedious and time-consuming process, requiring extensive research. Models have been used to estimate the optimum temperature (Bai et al., 2010; Zhao et al., 2017) and sowing date (Dobor et al., 2016; Freitas et al., 2019) for maize crops, albeit with a focus on different scenarios. Determining the right sowing date ensures that the SDI with DI yields and yield components are maximized, high irrigation linked with maize is minimized, and the environment is protected.

Models serve as representations of processes and events in the form of mathematical equations and expressions; given the right set of data, they can simulate and optimize the scenario under observation. Agricultural models have been in use for several years, and their popularity have been steadily increasing (Long et al., 2006; Asseng et al., 2013). Well-calibrated models have successfully estimated crop yields for various plants, including knapsack (Difallah et al., 2017), rice (Boonwichai et al., 2018), wheat (Guillaume et al., 2016, Cilek and Berberoglu, 2019), maize (Linker and Kisekka, 2017; Kaur and Arora, 2018), cotton (Li et al., 2019; Ale et al., 2020) and soybean (Barker et al., 2019; Sharda et al., 2019).

In addition to paddy rice and a few other hydrophilic crops, maize is known for its high irrigation requirements (Brouwer and Heibloem, 1986). Due to the economic importance of maize as a widely cultivated cereal crop (Ranum et al., 2014; Dowswell et al., 2019), the reduction of maize irrigation requirements through the optimization of DI through careful selection of sowing dates and temperatures is crucial. This optimization not only mitigates moisture stress associated with these measures but also enhances the economic viability of maize cultivation. The SDI contributes to reducing maize irrigation requirements by preventing runoff and surface evaporation, enabling optimum yields in deficit irrigation applications (Douh and Boujelben, 2011; Irmak et al., 2016). Models have been deployed to maximize the benefits derived from combining SDI and DI (Himanshu et al., 2019).

The Cropping Systems Simulation Model (CropSyst) is a process-oriented simulation model that incorporates crop growth, management, and environment interactions. CropSyst estimates daily biomass accumulation, providing crucial plant parameters such as Leaf Area Index (LAI) and yield. This is achieved through several specialized modules that are coupled together to model plant growth and environment interactions (Stöckle et al., 2003). CropSyst holds an advantage over other models due to the ease of calibration with few parameters while maintaining high performance (Montoya et al., 2018; Luo et al., 2022). CropSyst has been effectively used to estimate maize yield under various conditions (Donatelli et al., 1997; Bellocchi et al., 2002; Sommer et al., 2007; Umair et al., 2017; Cilek et al., 2019). However, as far as our knowledge extends, optimizing and simulating maize yield with varying temperatures and sowing dates in the context of SDI and DI using CropSyst has not been thoroughly investigated and necessitates detailed exploration . This research aims to (1) Evaluate the yields of maize crops under SDI, and using the crop parameter to calibrate and validate CropSyst with climatic, soil, and management data (2) optimize DI yields through adjustments in both sowing dates and temperatures; and (3) predict the most efficient sowing dates and temperature ranges for deficit irrigation treatments.

MATERIALS AND METHODS

Site and Climate

The research was conducted at the Agricultural Experimental Station, Cukurova University, Adana, located in southern Türkiye ($37^0 00'54''$ N, $35^0 21'27''$ E; altitude 32 m). The site exhibits a gentle slope of less than 1%, featuring young soil with a silty loam texture classified as a Typic Haploxerert according to the USDA (Soil Survey Staff, 2014). The climate is characteristic of a Mediterranean climate, with mild and wet winters and hot and humid summers. Climatic data (Table 1 and Fig. 1) for the research area were obtained from the Adana Province meteorological station, located 3 km from the experimental station. The dataset comprised daily rainfall (mm), maximum and minimum temperature (°C), solar radiation ($MJ.m^{-2}$), minimum and maximum relative humidity (%), and wind speed ($m.s^{-1}$). Long-term (spanning over 90 years) climatic data for the region indicated a minimum temperature of 13.8 °C, a maximum temperature of 25.3 °C, an average temperature of 19.1 °C, and an annual average rainfall of 671.3 mm. The climatic data for 2017–2020 deviated from long-term climatic averages. The average temperatures for 2017, 2018, and 2019 ranged from 22.9-30.95, 23.69-30.21 and 25.06-30.28 °C, respectively, compared to long-term data ranging from 21.6-28.6 °C. However, there was no marked difference between 2017 and 2019 for most of the climatic data, although there was a slight decrease in the average temperature, solar radiation, and precipitation from July to September. In comparison, there was a steady increase in October. These variations indicate a shift in atmospheric conditions during specific months, indicating an increasing change in the atmospheric conditions of the area; similar observations were also made at other locations (Bhattacharya 2019; Naz et al. 2022). During the research period, there was light rainfall; as a precaution, the treatments were adjusted to the amount of rainfall during the research period.

Table 1. Long-term (90 years) average climatic information of the agricultural station.

	Months												Year
	1	2	3	4	5	6	7	8	9	10	11	12	
T_{avg} (°C)	9.4	10.5	13.4	17.5	21.7	25.6	28.2	28.6	26	21.6	15.8	11.1	19.1
T_{max} (°C)	14.7	16.1	19.4	23.7	28.2	31.7	33.8	34.6	33.1	29	22.5	16.7	25.3
T_{min} (°C)	5.1	5.9	8.2	11.8	15.7	19.7	22.9	23.3	20	15.6	10.6	6.8	13.8
R_t (mm)	111.6	89.7	65.4	51.9	48.8	22	10.2	9.8	19.6	43.6	71.4	127.3	671.3

$T_{avg:}$ average temperature; $T_{max:}$ maximum temperature; $T_{min:}$ minimum temperature; $R_{t:}$ total rainfall; 1–12: months in years

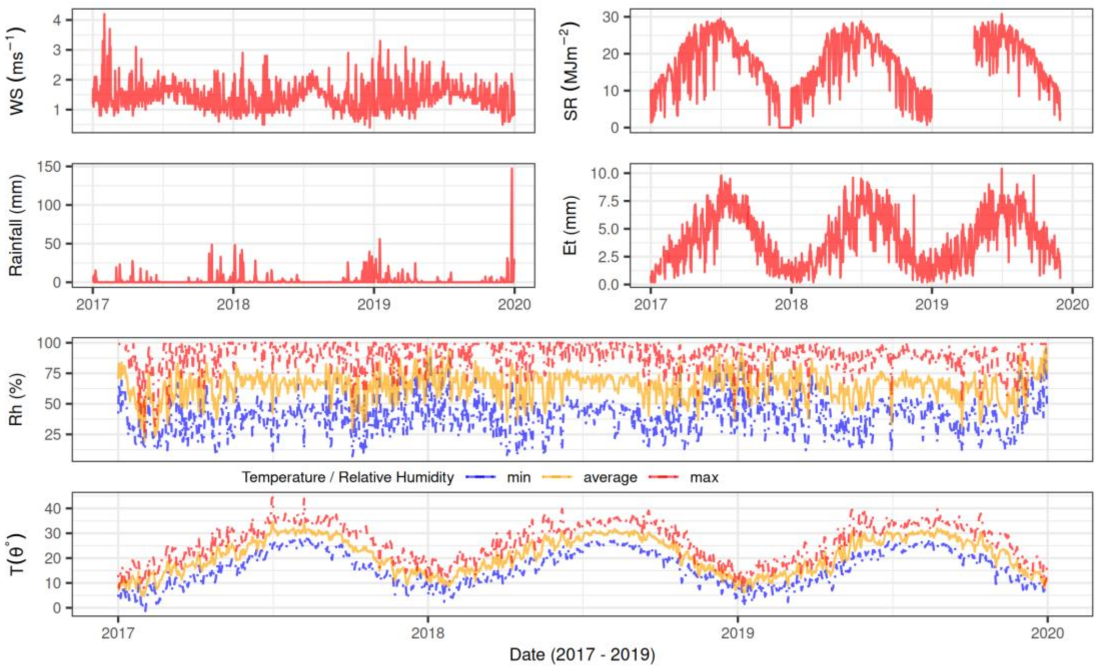

Figure 1. Climatic data (2017-2019) of the study area (T: temperature, Rh: relative humidity, WS: wind speed, SR: solar radiation, Et: evapotranspiration).

Experimental Setup

The experimental site was established in 2017 to irrigate high-value crops using SDI and possibly to conserve irrigation water in the region; detailed information can be found in Sariyev et al. (2020). The plot size of each parcel was 25.2 m^2 (6 m × 4.2 m), and each plot had 4 plant rows with 70 cm inter-row and 16 cm intra-row spacing and a distance of 1.5 m between each plot. The plants in each treatment group were allotted to each plot using a complete randomized design (CRD) with three replications. Generally, maize seeds are sown as a second crop, depending on the weather pattern to reduce rainfall interference and observe the effects of DI on SDI. Maize plants were harvested between October and November 2019, depending on the weather conditions. Irrigation treatments included I100 irrigation to field capacity (FC), serving as the control; I75 (75% of irrigation given to I100); and I50 (50% of irrigation given to I100). For 2017 and 2018, I75 was used as the I70, and I50 was included only for 2019.

SDI pipes were installed between rows of maize plants at a depth of 0.35 m below the soil surface, featuring pressure-compensated emitters with a 0.20 m spacing on the laterals. Drip emitters discharged irrigation water at 2 L h$^{-1,}$ which was a slight alteration to the methods of Irmak et al. (2016) to compensate for local soil properties. Soil moisture content was monitored with 30 cm long Time Domain Reflectometry probes (Time Domain Reflectometry, Soil Moisture TDR-6050X3K1B-MiniTrase Kit) buried at selected points between rows of maize plants, one pair per parcel. Treatments were reapplied when the soil available water content (AWC) in I100 reached 60% (Araya et al. 2016). An equal amount of irrigation was given to the crops to ensure uniform plant establishment in the first 2 weeks before the commencement of treatment. Irrigation was administered approximately every week, and in total 489 mm, 372 mm, and 255 mm of SDI were applied to I100, I75 and I50, respectively (excluding the pre-treatment irrigation). All other agronomic practices, including land preparation, fertilization, and weed and pest control, were uniformly applied across all treatments.

Data Collection

The agronomic data used for model calibration were collected in 2019. Yield and biomass data were sampled only once in 2017 and 2018 at physiological maturity, sourced from Sariyev et al. (2020). Data from these two years were only used for validating the calibrated model yields. From sowing to physiological maturity, different important plant physiological and morphological characteristics and the dates on which they occurred were recorded. In 2019, following the establishment of maize plants, initial plant sampling was carried out at 1 m^2 to measure the biomass and LAI at 3-week intervals after treatment started. At maturity, yield and final biomass were sampled from 6 m^2 area. Both yield and biomass were oven dried at 60 °C until a constant weight was reached. The LAI was measured with a LI-COR (model: Li-3100 area meter). The chemical properties of the soil used included the mean pH, electrical conductivity, percent calcium carbonate and, organic matter content, and cation exchange capacity, and were 7.57, 0.05 and m^{-1}, 315.0 g kg^{-1}, 15.1 g kg^{-1}, and 20.5 and 100 g^{-1}, respectively. The soil physical properties at the 0-30 cm soil depth included the mean bulk density (P_b), field capacity (θ_{vfc}), and wilting point (θ_{vwp}), which were 1.20 g cm $^{-3}$, 27.68%, and 19.58%, respectively.

Model

CropSyst is a comprehensive crop model comprising various submodels designed to estimate crop growth, the effects of crop development on soil, and their intricate interactions (Fig. 2). The parameters that are needed to calibrate CropSyst depend on the amount of data collected, and in addition to the CropSyst default parameters, estimating yield and plant growth parameters is much easier to calibrate compared to similar models (Stöckle et al. 2003; Rivington et al. 2007; Montoya et al. 2018). The model can also simulate long-term experiments, crop rotation, and crop productivity. CropSyst modules include CropSyst (modeling for crop growth and phenology, and calibration), Climgen (predicting climatic conditions of an area given sufficient previous year weather input), ArcCS (integrating CropSyst with ArcGIS maps for spatial modeling) and Watershed (groundwater modeling) (Stockle and Nelson 1994).

CropSyst also includes several additional submodels used for estimating various plant and soil processes. These submodels include the water budget, which can be estimated with either the Penman–Monteith model (Monteith 1965) or the Priestly Taylor model (Allen et al. 1998); the nitrogen budget includes the nitrogen cycle and symbiotic nitrogen fixation (Stockle and Campbell 1989); ammonium adsorption (Bouniols et al. 1991); and nitrogen plant uptake models (Godwin and Allan Jones 1991). The other submodels include crop phenology, biomass accumulation, leaf area growth, root growth, and yield. The details of the model components and equations used are extensively discussed in Allen et al. (1998). Use and parametrization were carried out as described by Stockle and Nelson (1994).

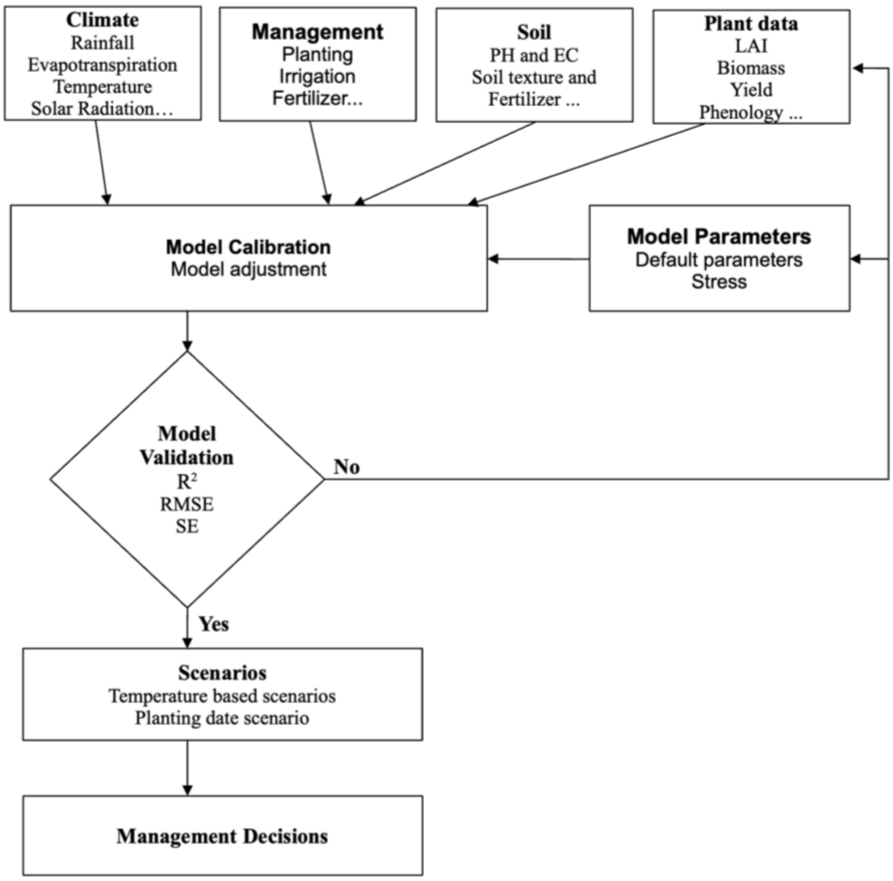

Figure 2. Flowchart of processes involved in implementing CropSyst (modified)

Model Calibration

For the unstressed calibration of the CropSyst model, data collected in 2019 (Table 2) from the I100 were used to calibrate the maize crop module in the CropSyst model to the conditions of the experimental area. The CropSyst calibration is crucial for obtaining accurate results (Bocchiola et al. 2013). The climatic data, which included the maximum and minimum temperatures, maximum and minimum relative humidity, solar radiation, and rainfall, were entered into the weather editor for 2017–2019. The model was initialized to initial soil conditions by incorporating soil data, which included the thickness of the soil layers, the particle size distribution of the soil (sand, silt, and clay), the pH, the cation exchange capability (CEC), the bulk density, the moisture content (field capacity and wilting point) and the saturated hydraulic conductivity.

Management data reflecting actual field practices included irrigation dates and volumes, irrigation and fertilization methods, and harvest dates. Plant morphological data, which included LAI, biomass and, phenological data, which included the base temperature, emergence date, maximum LAI, flowering date, filling date, and physiologic maturity date, were converted by the crop model submodule to Growth Degree Days (GDD). Parameters such as the fraction of LAI_{max} at physiological maturity, maximum rooting depth, evapotranspiration at full canopy, maximum water uptake, leaf water potential that stops canopy expansion, leaf water potential that begins to reduce canopy expansion, and wilting leaf water potential were not altered. Furthermore, default values such as leaf area duration, extinction coefficient, transpiration use efficiency, vapor density (VPD) at 1 kPa, and photosynthetically active radiation were adjusted until the measured data were close to the modeled data. This was achieved by taking the root mean square error (Eq. 1), the standard error (Eq. 2), the P significance levels and the R^2 (regression coefficient) of their regression outputs.

$$RMSE = \sqrt{\frac{1}{n}\sum(mo_i - me_i)^2} \tag{1}$$

RMSE = Root mean square error, mo = modeled, me = measured, n = sample size

$$SE = \frac{\sigma}{\sqrt{n}} \tag{2}$$

SE = Standard Error, σ = standard deviation, n = sample size

Model Validation

Validation was performed by comparing the yield and biomass for I100 and I75 for 2017 and 2018 through percent deviation (Eq. 3).

$$percentdeviation = \frac{(me_y - moy)}{me_y} * 100 \tag{3}$$

me_y = measured yield, mo_y = modeled yield

Table 2. Parameters used in calibrating the CropSyst model

Parameter	Value	Method	Units
Phenology			
GDD emergence	93	O	ºC days
GDD LAI	807	O	ºC days
GDD Flowering	892	O	ºC days
GDD Filling	1079	O	ºC days
Physiologic maturity GDD	1759	O	ºC days
Base temperature	6	R	ºC
Cutoff temperature	23	R	ºC
Phenological sensitivity to water stress	1	M	-
Morphology			
Specific leaf area	24	C	m^2 / m^2
Fraction of LAI_{max} at physiological maturity	0.8	M	-
Maximum LAI	5	O	m^2 / m^2
Maximum rooting depth	1.5	M	m
Stem/leaf partition coefficient	3.5	C	m^2 / kg
Leaf area duration	1000	C	ºC days
Canopy extinction coefficient for global radiation	0.5	C	-
Et at full canopy	1.3	M	-
Growth			
Photosynthetic pathway	C4	-	-
Transpiration use efficiency when VPD is at 1 KPa	8.5	C	g BM / Kg H_2O
Optimum temperature for growth	18	M	ºC
Photosynthetically active radiation	4.5	C	g / MJ
Maximum water uptake	14	M	mm / days
P_w at onset of stomata closure	-1200	M	- J / kg
Wilting leaf water potential	-1800	M	- J / kg
P_w that begins reduction of canopy expansion	-800	M	J / kg
P_w that stops canopy expansion	-1200	M	J / kg

R: published article. O: observed, M: default values, C: calibrated, GDD: growth degree days, LAI: leaf area index, VPD: vapor density, Et: evapotranspiration, P_w: plant wilting

Scenarios

The scenarios considered included a reduction in sowing date scenario (RSDS): 1 wk interval, from the 1st wk to the 13th week before the actual sowing date for each simulation; two levels of temperature regimes, namely, a constant temperature scenario (CTS) from 23 °C to 40 °C with a 1 °C increase interval for each scenario; and an average daily temperature increase scenario (ADTIS) from 0 to 10 °C with a 1 °C increase interval for each simulation. These scenarios were maintained for all developmental and anthesis stages, and selectively during the anthesis stage. These two main scenarios were selected to optimize deficit irrigation applications and test the sensitivity of CropSyst to different temperature and sowing date conditions.

Statistical Analysis

All the statistical analyses were performed in R 3.1.10 (R Core Team 2021). Analysis of variance (ANOVA) was used to test for significant differences between treatments, and the Agricolae package was used (Mendiburu 2021) for separation of means using the least significant difference (LSD) test. The data were plotted with ggplot (Wickham et al. 2021) and its associated derivatives. Model output was compared through linear regression, and major modeling parameters, such as the root mean square error (RMSE), regression coefficient (R^2), standard error (SE), and *P,* were extracted using the broom package (Robinson et al. 2021).

RESULTS

Biomass, Leaf Area Index and Yield

The irrigation treatment did not cause any significant changes in the plant biomass used in the calibration of CropSyst (Table 3). The plant biomass varied with I50 < I75 < I100 and I100 generally had the highest plant biomass throughout the sampling period. Also, the LAI (Table 3) was also not significantly affected by the SDI except at the second sampling stage, the LAI varied according to I75 < I50 < I100, with I100 having the highest LAI values across the different sampling dates.

Irrigation treatments significantly improved the maize yield (Table 4) used in calibrating CropSyst. The yields for 2017 and 2018 were obtained from Sariyev et al. (2020). The lowest yield in I100 was in 2018, which was lower than that in 2019. There was a sharp increase in the I75 maize yield in 2019 when the result was compared to the maize yields for 2017 and 2018, despite the low difference in irrigation between the treatments for the different years (5%).

Table 3. Summary of the biomass data for 2019 used in the calibration of the model.

Treatment	Biomass (t ha^{-1}) 2019			
	22/08/2019	18/09/2019	02/10/19	11/11/19
I100	6.97$^{\#}$ ± 0.76†	15.56 ± 0.67	29.24 ± 0.96	31.92 ± 7.08
I75	6.79 ± 0.57	14.52 ± 1.06	28.93 ± 2.45	33.48 ± 3.49
I50	6.97 ± 0.66	14.21 ± 1.30	27.73 ± 2.23	27.59 ± 6.23
LSD	ns	Ns	ns	ns
	LAI (m^2 m^{-2})			
I100	4.93$^{\#}$ ± 0.43	4.69 ± 0.12 a$^{\&}$	4.36 ± 0.37	2.92 ± 1.10
I75	4.52 ± 0.20	4.05 ± 0.07 b	3.48 ± 0.71	2.45 ± 0.59
I50	4.72 ± 0.59	4.61 ± 0.37 a	4.00 ± 0.69	1.69 ± 0.28
LSD	ns	0.46*	ns	ns

$^{\#}$ The average of the different samples collected for I100, I75, and I50, † the standard deviation for the different sample collected, and LSD, the least square differences of each treatment after ANOVA has been carried out. 07/08/2018-11/11/2019 represent the different dates on which the samples were taken; ns indicates that the differences among the treatments were not significantly different, and * indicates that the treatments were significantly different (P < 0.05).

Table 4. The mean yield of maize under SDI and DI for 2017-2019.

Treatment/year	Yield (t ha^{-1})		
	2017	2018	2019
I100	11.15	9.74	12.32$^{\#}$ ± 0.83† a$^{\&}$
I75/I70	6.44	6.31	10.99 ± 1.16 ab
I50	-	-	9.41 ± 1.19 b
LSD	-	-	1.83**

$^{\#}$ the average of the different samples collected for I100, I75, and I50, † the standard deviation for the different sample collected, and LSD, the least square differences of each treatment after ANOVA has been carried out. 07/08/2018-11/11/2019 represent the different dates on which the samples were taken, and there were significant differences among the treatments; ** indicates highly significant differences (P < 0.01).

Model calibration and validation

The most important calibration was in the CropSyst plant module. The climatic data and the dates on which they occurred were used to estimate the growing degree days (GDD) values. The GDD emergence, maximum LAI, flowering, filling, and physiological maturity were 93, 807, 892, 1079 and 1759, respectively. The maximum LAI from the field experiment was 5.0 m^2 m^{-2}. The leaf area duration of 1000 GDD was obtained from the field study, and the canopy extinction coefficient for the global radiation default value model was calibrated to a default value of 0.5.

The regression analysis for the CropSyst model (Fig. 3 and Table 5) showed high regression coefficients for both biomass and LAI. The highest regression coefficient was obtained for I100, with I75/70 and I50 also within similar ranges.

Table 5. Statistical indices used to measure the performance of the model in relation to the biomass and LAI of the observed and measured treatments.

	Treatments	R^2	RMSE	P	SE
	I100	0.91	4.51	0.01*	13.07
Biomass	I75	0.87	5.66	0.02*	13.53
	I50	0.88	4.56	0.02*	11.59
	I100	0.80	0.47	0.04*	0.91
LAI	I75	0.90	0.28	0.01*	0.80
	I50	0.51	0.93	0.18ns	1.15

R^2 regression coefficient, RMSE in t ha^{-1} root mean square error, $p < 0.05$ the probability that the difference between the measured and the modeled values is greater than 0,*significant, SE standard error measured in t ha^{-1}

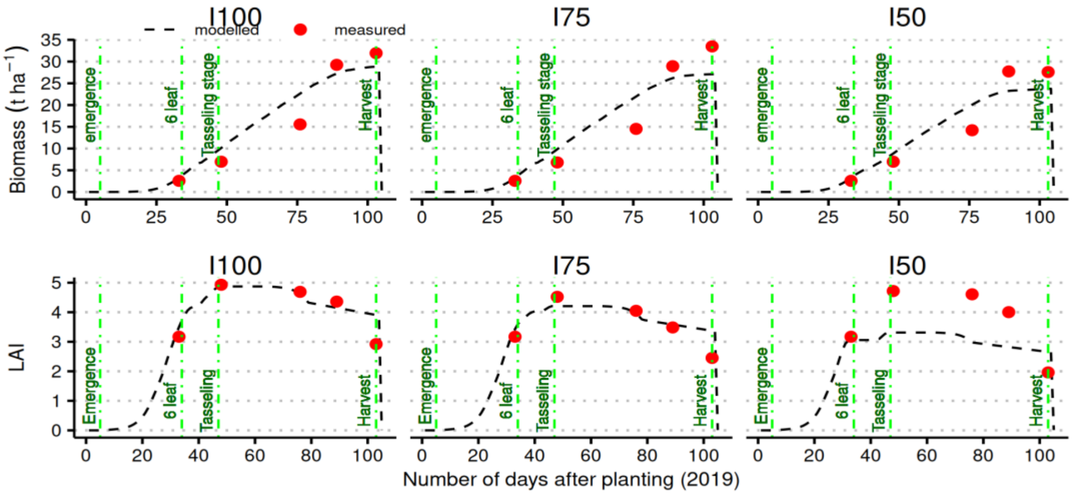

Figure 3. Graph of the modeled and measured biomass (A) and LAI (B) according to the alteration in the different sowing dates of the maize crop.

The R^2 and RMSE (Fig. 3 and Table 5) values were similar for both the biomass and LAI. The lowest performance was observed in the I50 LAI regression coefficient, having a R^2 value of 51% (acceptable limit 70%), and a high RMSE, indicating a high residual error between the modeled and the measured LAI. Furthermore, the poor regression line between the modeled and the measured LAI ($P > 0.05$) also supports this assumption. According to the LAI regression analysis, I75 had the highest R^2, the lowest RMSE and SE and a good regression line between the modeled and the measured values ($P < 0.01$). The biomass calibration result shows that I100 has a good fit with an R^2 of 90%; a good regression line between the measured and the modeled and measured values ($P < 0.01$) and the lowest RMSE, I50 and I75 also had good regression lines ($P < 0.05$) and R^2 greater than 87%. All the modeled yields (2019) obtained from the CropSyst calibration were slightly underestimated. The model performance result indicates that I50 > I75 > I100 (Table 5).

The model was validated with only the yield obtained from 2017 and 2018 (Table 6), and the percentage deviation was given as a measure of difference between the measured and modeled values. The model accurately modeled I100's maize yield for 2017, with a percent deviation of only 0.62% (slight overestimation), and it was overestimated by -13.73% in 2018. In summary, the I100 yield can be estimated with ±14% accuracy with the calibrated model. An average 39% overestimation was estimated for I75 in 2017 and 2018.

Table 6. Contrast between the modeled and measured yields for 2017–2019.

Years	Treatment	Measured (t ha^{-1})	Modeled (t ha^{-1})	Percent deviation
	I100	11.15	11.22	0.62
2017	I70/I75	6.40	10.66	39.96
	I50	-	-	-
	I100	9.74	11.29	13.73
2018	I70/I75	6.53	10.74	39.2
	I50	-	-	-
	I100	12.32	11.31	-8.93
2019	I70/I75	11.00	10.63	-3.48
	I50	9.41	9.31	-1.07

Modeled is the estimate obtained from the CropSyst model, while measured is the actual measurement from the field

Scenarios

Sowing date and temperature optimization scenarios were carried out with the calibrated and validated models. The yield of the model optimized for the sowing date (RSDS) was different from that of the actual sowing date. Generally, the

RSDS results (Fig. 4 and Table 7) suggest that CropSyst can be used to optimize the sowing date of maize under SDI with DI treatments. I100 had the least changes in yield; by adjusting the sowing date backward by 1-2 months, 10-15% yield increase could be obtained. However, the optimized model indicated that the appropriate sowing date could be in 11/05/2019 for I100, for I75 adjusting the sowing date backward by 8 weeks, a 15% increase in yield would likely be obtained. Furthermore, the yield gap between I100 and I75 would have decreased and I75 productivity would have increased. The highest yield increase was simulated in I50, and by adjusting the sowing date backward by 9 weeks, close to 20% increase yield could be obtained.

The CTS yield and biomass estimates (Fig. 4 and Table 8) gave varying levels of results. The CTS result indicated that the I75 yield and yield components could be improved. The I75 yield increased with increasing CTS interval. However, the yield and yield components for I50 decreased from the beginning of the simulation, and there was no improvement with increasing simulated temperature. The CTS caused an increase in yield till the upper limits of the simulated scenario, after which a steady decline in yield was obtained. The CTS scenario indicated that the I50 peak yield ranged from 25-27 °C, while the I75 and I100 peak yields ranged from 28-30 °C and from 30-35 °C, respectively.

Table 7. The outputs obtained from the RSDS scenario.

Treatment	Sowing date	Biomass (t ha^{-1})	Yield (t ha^{-1})
I100	06.07.19	28.84	11.31
	15.06.19	32.33	12.68
	25.05.19	33.52	13.15
	04.05.19	34.11	13.38
I75	06.07.19	27.10	10.63
	15.06.19	31.65	12.41
	25.05.19	28.58	11.21
	04.05.19	32.72	12.83
I50	06.07.19	23.74	9.31
	15.06.19	28.49	11.17
	25.05.19	25.57	10.03
	04.05.19	29.33	11.50

The sowing date indicates that different date scenarios were carried out to optimize the model for the most appropriate sowing date.

Table 8. Outputs for the different temperature adjustment scenarios throughout the growing cycle and during the tasseling stage.

Treatments	Temperature, °C	Biomass	Grain yield	Biomass	Grain yield
		CTS (all stages)		CTS (tasseling and flowering)	
		t ha^{-1}			
I100	23	25.12	9.85	-	-
	27	27.69	10.86	28.61	11.22
	31	29.14	11.43	28.72	11.27
	35	29.16	11.44	28.72	11.27
	40	27.09	10.63	28.72	11.27
I75	23	25.12	9.85	-	-
	27	27.33	10.72	26.70	10.47
	31	27.39	10.74	26.90	10.55
	35	24.56	9.63	26.90	10.55
	40	22.15	8.69	26.90	10.51
I50	23	24.96	9.79	-	-
	27	25.75	10.10	23.06	9.04
	31	23.79	9.33	23.37	9.16
	35	21.09	8.27	23.34	9.16
	40	17.60	6.90	22.82	8.95

The temperature (a constant temperature is maintained for every scenario, and the summary is given for every 4 °C)

Table 9. The output for the ADTIS scenario

Treatment, °C	Tavg +	Biomass	Grain yield	Biomass	Grain yield
		Throughout life cycle		Tasseling stage	
		t ha^{-1}			
I100	0	28.72	11.27	28.72	11.27
	3	29.06	11.40	28.72	11.27
	6	28.60	11.22	28.72	11.27
	9	-	-	28.72	11.27
	10	-	-	28.72	11.27
I75	0	26.90	10.55	26.90	10.55
	3	25.05	9.83	26.90	10.55
	6	23.24	9.11	26.90	10.55
	9	-	-	26.90	10.55
	10	-	-	26.90	10.55
I50	0	23.35	9.16	23.35	9.16
	3	21.50	8.43	23.34	9.16
	6	19.74	7.74	23.25	9.12
	9	-	-	22.78	8.94
	10	-	-	22.69	8.90

T_{avg} (the average atmospheric temperature is increased by 1 °C each without maintaining a constant temperature compared to the previous scenario) – the yield remains constant above this temperature

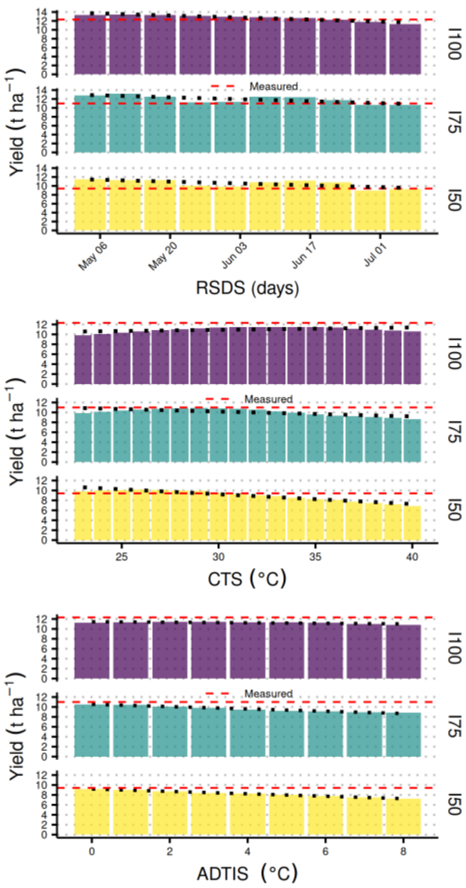

Figure 4. Reduced sowing date scenario (A), constant temperature scenario (B), and average daily temperature increase scenario (C)

The optimization ADTIS, (Fig. 4 and Table 9) did not improve the yield of I100, as it was relatively constant for all simulated temperatures. The optimization for I75 and I50 with ADTIS caused an overall yield reduction. A 2 °C increase in temperature marginally reduced the yields of both I75 and I50, signifying that a 1 °C increase in atmospheric temperature can influence maize yields with deficit irrigation. The impact of these changes was moderate when, the temperature was increased by 4 °C, the yield of I75 and I50 decreased to 10.43 t ha^{-1} and 9.16 to 9.51 t ha^{-1}, and 8.29 t ha^{-1}, respectively. The decrease was more acute with an 8 °C increase in the average daily temperature, and the simulated yields decreased to 8.84 t ha^{-1} and 7.23 t ha^{-1}, respectively. ADTIS applied during the tasseling stage did not change the yield of the treatments.

DISCUSSIONS

SDI Mitigates Yield Loss in Mild Deficient Irrigation

The lack of significant variation in plant biomass was due to the tolerance of Maize plants to moisture stress during plant growth stages, which may not negatively impact biomass or LAI (Irmak et al., 2022). Despite these findings, the yield and LAI in response to I100 were greater than those in response to the other treatments, especially toward the tasseling and maturity stage. More soil moisture may be required at late maize late development stages than at earlier vegetative stages (Comas et al. 2019), as other maize organs develop at this stage. Soil moisture is one of the factors limiting maize yield. Furthermore, moisture stress during the tasseling stage negatively affects the number of kernels on maize cobs and the size of maize kernels (Zhang et al., 2019; Zou et al., 2021).

There were only distinct differences between SDI treatments when irrigation treatments are less than 70% of full irrigation (I70), an indication that SDI mitigates water loss due to other irrigation methods (Irmak et al., 2016). This may only be achieved under moderate weather, which is unlikely to put much stress on maize plants (van Donk et al., 2013) and under certain conditions 60% of full irrigation could give yields equivalent to the yield of optimum irrigation (Vories et al., 2009).

Calibration of Cropsyst Is Feasible Except at Low SDIs

The GDD values in the phenology section (Table 2) were in accordance with the findings of Bellocchi et al. (2002). A base temperature of 6 °C and a cutoff temperature of 23 °C were selected according to Stockle and Kiniry (1990). The maximum LAI for regular season maize field trials is reportedly above 4.5 m^2 m^{-2} (Gong et al., 2017; Kukal and Irmak, 2020). However, Bellocchi et al. (2002) observed a greater maximum LAI in their field experiment. The GDD obtained was also used by Lenka and Singh (2011), in contrast a default leaf area duration of 800 GDD days is also possible Bellocchi et al. (2002). A leaf area duration below or above the default value can also be obtained from the model. This depends on the climate, management and the cultivar of the maize used. Bocchiola et al. (2013) and Eitzinger et al. (2013) estimated 650 GDD days from their calibrations, while Umair et al. (2017) reported 850 GDD days. The canopy extinction coefficient for global radiation default values was calibrated to 0.45 (Ambrona et al., 2013), a higher value of 0.6 is also possible (Cilek and Berberoglu, 2019). The different calibrated parameters suggest that calibrated models are unique to the climatic and field data used. The high R^2 from the validation result also suggests that the right field data calibration could give a high correlation coefficient (Stockle et al., 1997; Cilek and Berberoglu, 2019) and therefore be used to estimate plant biomass and LAI.

The result obtained from LAI calibration in I50 indicates that CropSyst may not accurately predict the maize LAI when SDI is less than 70%. Similarly, in a CropSyst calibration, a R^2 lower than 70% for LAI was obtained in the second year of a pivot irrigation system (Montoya et al., 2018). Conversely, low deficit irrigation LAI calibration (40% of irrigation requirement) had a high R^2 (Cilek and Berberoglu, 2019), which may be attributed to the different irrigation method from which the LAI data was obtained from (Yadav et al., 2024). The SDI is an excellent method for conserving irrigation water when properly administered, providing a higher plant parameter performance, especially under a limiting soil moisture conditions (Irmak et al., 2016).

The 39% overestimation in I75 yields in 2017 and 2018 was expected due to the difference between these two years and 2019. This was attributed to the irrigation frequency adopted in 2017 – 2018 and the atmospheric conditions, which negatively affected I70/I75 yield. Low irrigation and increased irrigation frequency intervals negatively impact the cowpea yield (Freitas et al., 2019) and maize yield at certain important physiological stages (Farré and Faci, 2009) in contrast to their irrigation requirements. The calibration results indicated that CropSyst can be calibrated for biomass and LAI at moderate soil moisture levels. This is further supported by different deficit irrigation levels in a pear orchard field experiment, where a high regression coefficient was obtained between measured and modelled yield (Marsal and Stöckle, 2012) and in wheat (Noreldin et al., 2015; Morsy et al., 2018). Considering the low regression coefficient obtained from the I50 LAI, CropSyst may not have accurately estimated SDI yields due to the high percent deviation obtained for the I75/I70 deficit irrigation treatments for both 2017 and 2018, despite the successful calibration.

CropSyst Is Limited to Full Crop Simulation

The sowing date has a direct effect on the yield of various crops, which is commonly attributed to unfavorable germination and early-stage growth conditions. These conditions can impede seed germination and induce stress in young plants at early growth stages, increasing the probability of crop failure or poor yield performance (Kucharik, 2008; Jasemi et al., 2013; Tsimba et al., 2013). The RSDS simulation results indicate that revision to planting dates can further improve maize yield. Early sowing of maize reduces yield loss in DI, and yields can be improved by simulating the planting date for maize (Abraha and Savage, 2006; Jalota et al., 2010). The changes in the crop yield can be explained by the climatic data recorded during the growth stages. The peak evapotranspiration in 2019 occurred during the sowing date and remained relatively constant during the growth stages. However, I100 actual transpiration was close to the potential evapotranspiration of 6.58 mm; the other treatments were likely under moisture stress. Adjusting the sowing date backward reduced the stress on DI treatments, leading to better yield performance. The results from the RSDS scenario suggest that CropSyst may be used to further improve DI through adjustment in planting date, which further reduces the yield loss associated with DI applications.

The CTS simulates the temperature ranges to which the optimum yield can be obtained for DI treatments. This approach can be used in combination with the RSDS scenario, because sowing date is one of the factors affecting plant growth and yield. The temperature ranges obtained from the CTS scenario can be used with yearly weather forecasts to determine the appropriate planting date that will ensure conducive growing conditions for maize plants. This could prevent crop failure that is likely to occur under DI treatments, as high temperatures may subject maize plants to moisture stress due to high evapotranspiration rates, leading to early termination of crops. Similar to the RSDS scenario, I100 was also underestimated under the CTS scenario, while the other I75 and I50 treatments attained measure yields. The tasseling stage (Çakir, 2004; Ge et al., 2012) and the silk stage Baum et al. (2019), collectively known as the the anthesis stage, were considered due to their importance to maize yield. However, the optimization performed through the CTS scenario during the maize anthesis stage did not affect the modeled yield as model outputs remained relatively constant.

The ADTIS simulation (Fig. 4 and Table 9) could not improve the I100 yield, remaining relatively constant for all the simulated temperatures. In contrast, high atmospheric temperatures above 38 °C reduces maize photosynthetic capabilities, resulting in lower maize yields (Crafts-Brandner and Salvucci, 2002; Lobell et al., 2011). This finding indicated that CropSyst may not be able to simulate maize yield for I100 yield when the average daily temperature is increased above the maximum daily temperature. In contrast, Ma et al. (2017) reported a 21% decrease in yield with the RZWQM2 model and to a lesser extent a decrease of 14% in DI yields. However, I75 and I50 yields were reduced with increasing scenario simulations; the DI yields reduction in ADTS was attributed to temperature-related soil moisture-induced stress, making CropSyst a viable tool for simulating similar scenarios. This simulation explains soil moisture stress in deficit irrigation treatments in maize plants when atmospheric temperature changes in spring (Farré and Faci, 2009). Furthermore, a 3-5% reduction in wheat yield was predicted when the average daily temperature increases by 1 ºC in DSSAT (Ding et al., 2021). The scenario indicates that CropSyst could simulate temperature changes in maize yield in deficit irrigation.

The ADTIS simulation could not simulate the effects of temperature changes for the tasseling stage for all the irrigation treatments. Conversely, temperature-induced stress during the tasseling stage negatively affects the number of kernels in a cob leading to yield loss (Tollenaar and Bruulsema, 1988; Hatfield and Prueger, 2015). Furthermore, CropSyst also poorly simulates stress-related yield loss during the flowering stage compared to DSSAT, EPIC, WOFOST, AQUACROP, FASSET, and HERMES (Eitzinger et al., 2013). This may limit the use of the model to simulate certain crop stages and, especially certain maize development stages that are critical to maize yield.

CONCLUSION

CropSyst, a widely used tool for simulating yield and biomass under various conditions, was effective in the simulation of maize yields with SDI and DI under different temperatures and sowing dates. This underscores its significance as a crucial instrument for optimizing maize yields under DI scenarios. The calibration results indicate that CropSyst performed well in the estimation of most of the treatments. The control scenario (irrigation to field capacity) was accurately simulated for both 2017 and 2018, although DI treatments were somewhat overestimated for the same period.

Optimizing the planting dates and temperatures for the calibrated and validated data yielded promising results. Simulating the most suitable sowing date optimized the DI yields, serving as an alternative to their full irrigation requirement and also further highlights the need to carefully select the right sowing dates for DI applications. Adjusting the sowing date by one or two weeks for DI treatments caused notable improvements in DI maize yields. Furthermore, temperature optimization underscored the importance of aligning the growing season with specific temperature ranges. While there was an increase in the plant yield for the simulated sowing dates, the simulation for the different temperatures increased the yield to tolerable levels before the gradual decline. In other scenarios the yields decreased throughout the simulation period (increase in the average daily temperature). In summary, CropSyst exhibits sensitivity to temperature variations in maize growth under SDI and DI. A properly calibrated and validated CropSyst model is valuable for simulating and optimizing the most suitable sowing date and temperature range, enhancing maize yield DI performance. To further refine estimations of maize yield, biomass and LAI under SDI and deficit irrigation conditions, additional efforts should focus on fine-tuning the water budget module to consider SDI systems at very low DI levels. Further research in this direction holds considerable promise for advancing the capabilities of the CropSyst model.

Compliance with Ethical Standards

Peer Review

This article has been reviewed by independent experts in the field using a rigorous double-blind peer review process.

Conflict of Interest

The authors declare no conflicts of interest.

Author Contributions

Conceptualization, T.S.W., A.S. and C.B.; methodology, T.S.W., A.S., M.A. and C.B.; investigation, T.S.W. and M.A.; writing—original draft preparation, T.S.W., M.A. and A.Ç.; All authors have read and agreed to the published version of the manuscript.

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