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Determination of Optimal Water Requirement for Sweet Corn Crop Based on Meteorological Data and Plant Growth Parameters

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ABSTRACT

Maize (*Zea mays* L.), or corn, is the world's leading cereal crop and ranks third in importance after rice and wheat. It is a primary food source for humans and livestock and a raw material in various industries. To reduce dependence on corn imports, Malaysia has initiated large-scale local cultivation. However, the maize industry faces challenges from waterlogging and water scarcity due to the tropical climate, which causes droughts and floods, impacting maize production. This study aims to improve crop water requirement (CWR) estimations for maize using CROPWAT, considering growth stages and soil variability, and validate irrigation management strategies. Based on 30 years of climatic data from MetMalaysia, evapotranspiration (ET_c) was estimated using CROPWAT V8. Experimental plots with four irrigation water application (IWA) treatments were used to validate ET_c: T1 (50% ET_c), T2 (75% ET_c), T3 (100% ET_c), and T4 (125% ET_c). Crop growth parameters were assessed at four growth stages: plant height, stem diameter, shoot fresh weight, and kernel moisture. Results showed T4 (451.07 mm/season) had the highest growth rate and met all hybrid corn growth standards set by the Department of Agriculture, Ministry of Agricultural and Food Security (MAFS). In contrast, T3 (100% ET_c) was insufficient for sweet corn, failing to meet several standards. Thus,

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E-mail addresses: noorellimia@upm.edu.my (Noorellimia Mat Toridi) maleqisqandar@gmail.com (Muhammad Maleq Isqandar Nor Jalal) aimrun@upm.edu.my (Aimrun Wayayok) mohdazwan@upm.edu.my (Mohamed Azwan Mohamed Zawawi) *Corresponding author T4 (125% ET_c) proved the most effective IWA practice, particularly for areas within a 30 km radius of the Subang weather station.

Keywords: Corn, crop water requirement, CROPWAT, evapotranspiration, growth parameters

INTRODUCTION

According to information from the Malaysia Department of Agriculture, the production

ISSN: 0128-7680 e-ISSN: 2231-8526 cost of maize in Malaysia was \$84.00 per ton in 2012. While global demand for maize was on the rise, there was uncertainty about whether a future supply could meet the growing demand. Increasing imported maize prices raised economic concerns in Malaysia, as highlighted by Soleymani and Shahrajabian (2018). The government acknowledged the difficulties faced by the industry, including constraints such as limited arable land, unfavorable weather conditions for corn cultivation and water scarcity. The high water requirements, along with susceptibility to drought and heat, were negatively impacting corn productivity.

In Malaysia, both droughts and floods further complicate agricultural production. Droughts, often associated with the Southwest Monsoon, exacerbate water scarcity, while floods, particularly during the Northeast Monsoon, can damage crops and disrupt farming. These weather extremes, driven by Malaysia's tropical climate, are making it increasingly difficult to maintain stable maize production.

Water scarcity, exacerbated by climate change and competition from various sectors, was a significant barrier to maize cultivation in non-irrigated areas (Song et al., 2010). This scarcity restricted agricultural growth and reliability. It became crucial to accurately determine crop water requirements to mitigate these issues. However, the current estimation methods pose challenges for water utilities' distribution systems, leading to uncertainty and the potential need for unnecessary infrastructure expansion.

Crop Water Requirement (CWR), also known as crop evapotranspiration (ET_c), is the amount of water a specific crop needs over its entire growing season to meet its evaporation and transpiration needs. The reference evapotranspiration (ET_c) is often used as a basis, and crop coefficients (K_c) are applied to adjust ET_o for specific crops and their growth stages. These coefficients play a crucial role in accommodating the diverse water requirements of different crops throughout their growth cycles. In their study, Gamal et al. (2022) utilize an energy balance approach to estimate ET, where latent heat exhibits a similar pattern to daily ET observed at research stations. Concurrently, the determination of crop coefficients (K_c) through unmanned aerial vehicle (UAV) remote sensing, as exemplified in the study by Parmar et al. (2023) and machine learning (ML) techniques, as discussed by Shao et al. (2023), has proven to be a viable approach for estimating cumulative evapotranspiration (ET) at various growth stages.

Various methods exist for estimating crop evapotranspiration (ET_c). In the study by Hong et al. (2022), the evapotranspiration of tomatoes was determined using the water balance method (ET_c), which includes irrigation as part of the water balance. Jie et al. (2022) provide a quantitative analysis of agricultural water requirements under different probabilities, employing a Copula function–Monte Carlo method (CFMC). Meanwhile, the SIMDual K_c model, introduced by Xuan et al. (2021), computes daily crop evapotranspiration (ET_c) by incorporating soil evaporation (Es) and transpiration (Tr), employing a soil water balance approach and a dual K_c method, introduced the SIMDual K_c model, which calculates daily crop ET_c by taking into account both Es and Tr, using the soil water balance and a dual K_c method.

Recent research has brought into focus the intricate and interconnected nature of estimating crop water requirements (CWR) through tools like CROPWAT. Ruan et al. (2020) illustrated how the diminishing water resources in the basin have exacerbated water stress in the SDB, while sensitivity analysis emphasized that fluctuations in CWR are primarily linked to climate change, a point reinforced by both Nie et al. (2023) and Saeed et al. (2021). They emphasize the necessity of implementing adaptable irrigation approaches that respond effectively to changing climatic conditions, with CROPWAT as a versatile tool for managing water resources. Furthermore, (Wang et al., 2020) have highlighted the geographical disparities in CWR, wherein ET_c exhibited distinctive patterns compared to effective rainfall in specific geographic regions.

Meanwhile, Feng et al. (2023) have highlighted the significance of soil structure in determining crop water requirements. This finding underscores the need for CROPWAT users to integrate soil properties into their models and irrigation plans, recognizing that soil type plays a crucial role in influencing CWR. On the other hand, Gabr (2022) provides insights into irrigation efficiency when water resources are available. Integrating knowledge about soil properties and selecting appropriate irrigation methods can lead to more accurate CWR estimation and irrigation planning.

Although there has been considerable effort to determine crop water requirements using models like CROPWAT, more effective water management practices are needed for maize due to its high water needs and sensitivity to drought and heat, which reduce productivity. Current methods, such as crop evapotranspiration (ETc), often have difficulty accurately predicting water needs across various growth stages and conditions. While advancements in remote sensing, machine learning, and models like SIMDual Kc and CROPWAT have improved estimations by accounting for factors like soil evaporation, transpiration, soil properties, and climate, these methods have not yet been fully applied to practical irrigation management, especially considering geographic and soil differences.

Therefore, the objectives of this study are (1) to improve the accuracy of CWR estimations for maize by integrating CROPWAT to account for variability in growth stages and soil properties and (2) to validate practical irrigation management strategies that utilize the refined CWR estimations through the experimental site.

MATERIALS AND METHODS

Overview of Methodology

Our primary goal is to improve the accuracy of CWR estimations for maize by integrating CROPWAT to account for variability in growth stages and soil properties. Based on

extensive prior research and comparative analysis, one of the most effective methods for estimating this requirement is utilizing FAO-CROPWAT 8.0. This process necessitates the inclusion of vital parameters, including climatic data, crop specifics and soil information. Concerning climatic data, these crucial values were sourced from the nearest weather station situated in Subang, Petaling, Selangor.

Simultaneously, crop-related data, such as crop coefficient at various growth stages, growth rates and yield reduction percentages, were obtained from secondary sources via an extensive literature review. Furthermore, soil data, encompassing soil texture type, were gathered through soil sampling analysis employing the sieve method. Upon the completion of this extensive data collection, the crop water requirement (ET_c) was calculated using the Penman-Monteith method within the CROPWAT 8.0 framework.

The second objective is to validate practical irrigation management strategies that utilize the refined CWR estimations through the experimental site. To achieve this, we conducted a Randomized Complete Block Design (RCBD) experiment at the Ladang 15 nursery greenhouse within the Faculty of Agriculture, UPM. Based on the estimated crop water requirement determined by CROPWAT, four different IWA (Irrigation Water Application) designs were applied to seven replicates of sweet corn, resulting in a total of 28 replications. These IWA treatments were designated as follows: T1 = 50% of the simulated ET_c, T2 = 75% of the simulated ET_c, T3 = 100% of the simulated ET_c and T4 = 125% of the simulated ET_c.

Throughout the growth period from March to June, various plant growth parameters such as the number of leaves, leaf length, plant height, stem diameter and the size or weight of the yield produced were meticulously recorded to analyze growth rates under different treatment conditions. Finally, the growth parameters for each distinct treatment were subjected to analysis using IBM SPSS Statistics (Version 23) via one-way analysis of variance (ANOVA) and Tukey post hoc test to ascertain the relationship between the quantity of IWA and the observed growth parameters. The study's flowchart in Figure 1 illustrates the research process.

Study Area

The experiment took place during a single growing season, starting in March 2023, at the Ladang 15 greenhouse in the Faculty of Agriculture at Universiti Putra Malaysia, situated in Selangor, Malaysia (Figure 2). The geographic coordinates of the location are approximately 2°59'11"N latitude and 101°44'13"E longitude. As per the 2023 climate data for Selangor, Malaysia, the area experiences tropical humid conditions. Selangor is known for its warm climate, with an average daily high temperature of 33°C throughout the year, providing favorable conditions for outdoor activities with an average water temperature of 29°C. The region receives most of its precipitation between April and December.



Figure 1. The flowchart of the study



Figure 2. The greenhouse at Nursery of Ladang 15, Faculty of Agriculture, UPM. The top view of the greenhouse was obtained from Google Earth (A). The side and front view with dimensions (B, C)

Determination of Crop Water Requirement

The utilization of water by crops exhibited a direct connection to crop evapotranspiration, commonly referred to as ET_c . The crop's water use, ET_c , could be determined by multiplying the reference ET_o by a crop coefficient, K_c . The CROPWAT 8.0 model had the capacity to calculate daily ET_c , provided that the necessary climatic, soil and crop data were also available.

It includes climatic data, such as temperature, rainfall, wind speed and humidity, which are crucial for calculating reference evapotranspiration (ET_o). Additionally, crop-specific data is required, such as the type of crop, planting dates, growth stages, crop coefficients and potential yield. Soil data, encompassing soil type, texture, infiltration rates and root zone depth, is also necessary to account for the soil's water-holding capacity.

Climatic Data

In the estimation of crop water requirements within CROPWAT, the software considers vital climatic data. It encompasses essential meteorological parameters such as temperature, precipitation, wind speed and humidity. These climatic factors play a fundamental role in the calculation of reference evapotranspiration (ET_o), a key component in determining a crop's water needs. Data on precipitation, maximum and minimum temperatures, relative humidity, wind speed and sunshine duration, as displayed in Table 1, were gathered from the Subang Jaya weather station during the period spanning from 1993 to 2022.

Table 1

Month	Min. Temp. (°C)	Max. Temp. (°C)	Humidity (%)	Wind speed (km/day)	Sunshine (hours)
January	24.0	32.6	78	120	6.1
February	24.1	33.4	77	129	6.6
March	24.6	33.7	78	137	6.7
April	24.8	33.7	80	136	6.6
May	25.1	33.6	78	140	6.7
June	24.8	33.3	77	145	6.2
July	24.6	32.8	76	151	6.3
August	24.5	32.8	76	153	6.1
September	24.3	32.7	78	145	5.5
October	24.3	32.7	79	149	5.6
November	24.2	32.3	82	132	5.0
December	24.1	32.0	82	127	5.1
Average	24.4	33.0	78.5	138.7	6.0

Average climate characteristics from 1993–2022 recorded by Subang Jaya weather, Department of Meteorology Malaysia (MetMalaysia)

ET_o was computed through the FAO Penman-Monteith method, incorporated into the CROPWAT program and denoted as Equation 1.

$$ETo = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T_a + 273} u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)}$$
[1]

Where: ET_0 is reference evapotranspiration (mm day¹), *T*, *G* and *R_n* are daily mean temperature °C at 2 m height, soil heat flux density (MJ m⁻² day⁻¹) and net radiation value at crop surface (MJ m⁻² day⁻¹), respectively. Also, U_2 , $e_s e_a$, $(e_s - e_a)$, Δ and γ represent wind speed at 2 m height (m s⁻¹), saturated vapor pressure at the given temperature (kPa), actual vapor pressure (kPa), saturation vapor pressure deficit (kPa), slope of the saturation vapor pressure curve (Pa/°C) and psychometric constant (kPa/°C), respectively (Halimi & Tefera, 2019).

Crop Data

CROPWAT relies on the integration of crucial crop-specific information to estimate crop water requirements. It includes details about the type of crop being cultivated, planting dates, various developmental stages of the crop, crop coefficients representing its water needs at different growth phases and potential yield expectations. These crop-specific parameters are crucial for CROPWAT to calculate the reference evapotranspiration (ET_o) and subsequently determine the crop's water requirement (ET_c) throughout its growth cycle.

Sweet corn typically undergoes four discernible growth stages: initial, development, middle and late. Each stage has a specific duration of 15, 20, 25 and 15 days, respectively, with a total growing period of 75 days. Fortunately, CROPWAT software provides valuable crop data for sweet corn, including crop coefficients, maximum root depth, depletion fraction and yield response factors for each stage, as detailed in Table 2.

Crop	Stage	Duration (Days)	Crop Coefficient	Maximum Root Depth (M)	Depletion Fraction	Yield Response Factor
Sweet	Initial	15	0.30	0.3	0.50	0.4
corn	Development	20	0.30-1.15		-	0.4
	Mid-season	25	1.15	0.5	0.50	1.3
	Late season	15	0.40		0.75	0.5

Table 2

Details of the crop data stored in the CROPWAT 8.0 software (Adapted from Ushkarenko et al., 2014)

Significantly, there was an increase in the crop coefficient from the initial to the midstage, followed by a decrease from the mid to late stages. Although the change in K_c was slight, it did not remain a consistent value within any growth stage, indicating the dynamic nature of seasonal crop water requirements. Furthermore, the ET_c values were observed to be relatively low at the beginning and end of the growth cycle, registering at 0.3 and 0.4, respectively, when the crops were in their early and late productive stages. In contrast, they were notably higher during the mid-stage at 1.08.

Soil Data

The CROPWAT system evaluates soil type and texture to determine water-holding capacity, affecting crop water availability. A sieve analysis (Figure 3a) uses multiple sieves to assess particle size distribution in granular soils, involving sieves with mesh sizes from 4.75 mm to 0.075 mm, a mechanical shaker, and other tools (Fomin et al., 2019). The hydrometer test (Figure 3b) determines particle size distribution in fine-grained soils (Alade, 2018). Data from these analyses are used to plot a particle size distribution curve, which helps classify soil type using the U.S.D.A Soil Textural Triangle. Additional soil information, such as field capacity, wilting point, and available water holding capacity, is obtained from secondary data within CROPWAT.



Figure 3. Figure 3a demonstrates the sieve analysis, while Figure 3b illustrates the hydrometer test

Experimental Design

The planting media, with a 3:2:1 ratio of topsoil, peat, and sand, was used to fill polybags to a height of 30 cm, with each polybag weighing approximately 10–15 kg. F1 Hybrida 301 sweet corn seeds were initially sown in plastic trays and nurtured for 10 days until fully developed leaves emerged. Subsequently, these 10-day-old, fully germinated seedlings were individually transplanted into polybags pre-treated with insecticide or nematicide to prevent insect disturbances.

The treatments were categorized into four levels of irrigation water application (IWA). The IWA was determined as a percentage of the crop evapotranspiration (ET_c) as shown in Equation 2 by considering 70% irrigation efficiency since the plants were cultivated individually in a polybag with a radius of 17.5 mm and an area of 96,211.28 mm². The specific IWA levels were defined as follows: $T_1 = 50\%$ of the simulated ET_c, $T_2 = 75\%$ of the simulated ET_c, $T_3 = 100\%$ of the simulated ET_c and $T_4 = 125\%$ of the simulated ET_c.

 $IWA = (ET_{c} \times T_{\%} \times A) / (I_{e} \times 1000)$ [2]

Where: IWA is Irrigation water applied for a particular treatment and stage (ml), ET_{c} , A, I_e are Crop evapotranspiration (mm), 96211.28 mm² and Irrigation Efficiency, 70%. Also, T_% is 50%, 75%, 100% or 125% of simulated ET_e.

The study was conducted within a greenhouse with a measurement of 9 meters by 5 meters, with a polycarbonate roof. Each treatment consisted of 7 replicates, leading to 28 experimental units. The experiment adhered to a Randomized Complete Block Design (RCBD), where 28 polybags containing different treatments were fully randomized, as shown in Figure 4. The experimental plot covered an area measuring 6.2 meters long by 2.45 meters in row width, totaling 15.19 square meters, with pots spaced approximately 0.7 meters by 0.3 meters apart. The plants were manually irrigated with a measuring cylinder following their designated IWA levels, starting one week after full germination and continuing until the harvest throughout the entire growing season from March to June.



Figure 4. Polybag plots arrangement. L = 620 cm, D = 245 cm, x = 30 cm and y = 70 cm

Plant Growth Monitoring and Measurement

The monitoring and measurement of plant growth involved continuous evaluation and tracking of the progress and development of plants. This procedure necessitated regular measurements of essential plant characteristics, such as leaf count, leaf length, leaf width, plant height, stem diameter and the eventual yield size or weight. These measurements were employed in this study to investigate the relationship between irrigation and the growth

and development of plants. Consequently, plant growth parameters were recorded every two weeks throughout the entire growing season, extending until the harvest.

Plant Height

Plant height was measured from the soil surface to the highest point of the arch created by the uppermost leaf, specifically when its tip was pointing downward. Figure 5 illustrates the process for measuring the height of a corn plant using a measuring tape.



Figure 5. The determination of plant height (A). Plant measurements were taken at the study site (B)

Stem Diameter

The stem diameter was assessed using an electronic steel caliper vernier positioned 10 cm from the stem base, as illustrated in Figure 6. Alternatively, the second stem node of the



Figure 6. The stem diameter was 10 cm from the soil surface (A). Stem diameter was measured using an electronic vernier caliper (B)

maize could also serve as the area of interest, following agronomists' recommendations. The vernier caliper featured an LCD digital display with a high precision of 0.01 mm and a tolerance of 0.02 mm.

Single Fruit Weight

The sweet corn ears (mature cobs of sweet corn plants containing edible kernels) were harvested and weighed, and the average values were calculated to represent the yield for each treatment. The single fruit weight (SFW) was measured using an electronic scale with a sensitivity of 0.01 g. At the end of the fruiting stage, fruits with uniform maturity and color were randomly selected for quality assessment.

Kernel Moisture Content

Kernel biomass measurement reveals corn plant water content, including kernel moisture (Gambín et al., 2007). Sweet corn, harvested at the "milk stage" (75–80 days after sowing), was processed by separating grains from different parts of the cob (Figure 7A, 7B). A 10 g kernel sample was weighed initially (Figure 7C, 7D) and dried for 24 hours at 110°C according to ISO 6540 and BS 4317. After drying, the sample's weight was recorded, and the moisture content percentage was calculated.



Figure 7. The kernels were tested by pinching them until "milk" liquid came out, which shows that they were ready and good to be harvested (A) Definition of corncob grain area (B) Sample preparation collected from center and extremities of the corncob (da Silva Timm et al., 2023) (C) Sample was placed into the drying oven (D)

Statistical Analysis

Plant growth data were analyzed using IBM SPSS Version 23. Levene's test checked if variances among irrigation treatments were equal, followed by ANOVA to find significant differences between treatment means. If ANOVA showed significant differences, Tukey's Honestly Significant Difference (HSD) test and Duncan's Multiple Range Test were used to identify specific pairwise differences. All post hoc and Pearson correlation tests were conducted at significant P ≤ 0.05 and P ≤ 0.01 , respectively.

RESULT AND DISCUSSIONS

Water Requirements

Properties of Planting Soil

The soil's particle size distribution was assessed using mechanical sieve and hydrometer tests, resulting in a grain size distribution graph, as shown in Figure 8. Based on USDA standards, the soil is composed of 36.97% silt, 5.31% clay, and 57.72% sand, classifying it as sandy loam. Key parameters such as permanent wilting point (PWP), field capacity (FC), rainfall infiltration rate, maximum rooting depth, and soil moisture were obtained from CROPWAT 8.0 and literature, with PWP at 140 mm/meter, FC at 30 mm/day, maximum rooting depth at 300 cm, and initial moisture values at 0% and 140 mm/meter, respectively.



Figure 8. The grain size distribution curve is based on sieve and hydrometer analysis of the planting soil

Reference Evapotranspiration.

In March, elevated temperatures, low relative humidity and strong winds significantly elevated radiation and evapotranspiration, recording 19.9 MJ/m²/day and 4.65 mm/day.

Conversely, lower temperatures, high relative humidity and weak winds significantly reduced radiation and evapotranspiration in December, registering values of 16 MJ/m²/ day and 3.65 mm/day.

The higher solar radiation levels resulted in increased evaporation rates, leading to elevated ET_{o} values, as illustrated in Figure 9. Throughout the corn's growth period, which spans from March to June, there was a noticeable reduction in both radiation and ET_{o} , with radiation declining from 19.90 MJ/m²/day to 17.5016 MJ/m²/day and ET_{o} decreasing from 4.65 mm/day to 4.22 mm/day.



Figure 9. The effect of climatic parameters on radiation and reference evapotranspiration, ET.

Crop Evapotranspiration

ET_c exhibited an increase during the early to mid-growth stages (Initial-Mid) but showed a slight decrease in the later stages (Mid-Late). These fluctuations could be attributed to the changing crop coefficient, which increased from the Initial to Mid stages but decreased from the Mid to Late stages. Notably, effective rainfall was not factored in, as the plants were cultivated within a greenhouse and received tap water exclusively. Consequently, the results indicated no rainfall during the entire experimental period, resulting in net irrigation requirements (NIR) equal to the total crop evapotranspiration, amounting to 251.1 mm. Due to the cultivation method in polybags, water losses such as runoff, seepage, evaporation and percolation during irrigation application were negligible. Figure 10 provides a visualization of the crop water requirement at specific intervals, accounting for a 70% irrigation efficiency.



Figure 10. Crop water requirement, ET_c for sweet corn based on the reference evapotranspiration with the respective crop coefficient by considering 70% irrigation efficiency

Irrigation Water Applied

According to Equation 2, the IWA (Irrigation Water Amount) is expected to be slightly higher than the ET_{c} (Crop Evapotranspiration), taking into account 70% irrigation efficiency. Furthermore, the quantities of IWA varied based on the different assigned treatments, which were 50%, 75%, 100% and 125% of ET_{c} for T1, T2, T3 and T4, respectively, as illustrated in Figure 11 below. The water supply pattern followed the same trend shown in Figure 11, increasing from 1 to 53 DAS (Days After Sowing) but decreasing from 54 to 75 DAS due to changes in crop coefficients (K_c).



Figure 11. IWA in milliliter (ml) was applied to the experimental plot for each treatment at specific DAS intervals

Plant Growth Assessment

Individual phytomers were closely examined from planting to harvest to assess how plants responded to the water supplied. While all plants displayed a high survival rate for approximately 2.5 months, the notable distinction lay in their growth rates, as depicted in Figure 12. Furthermore, variations among treatments became apparent in terms of plant height, stem diameter, single fruit weight (SFW) and kernel moisture content. These differences were subjected to statistical analysis using tests for homogeneity of variance, ANOVA (Analysis of Variance) and Tukey tests to ascertain the p-value and establish the significance of the disparities between treatments.



Figure 12. The growth of plants at the study site at 15 DAS (A), 30 DAS (B) and 75 DAS (C)

Plant Height

The study showed significant variation in plant height across different stages. During 15 Days After Sowing (DAS), early growth focused on root and leaf development. ANOVA results indicated significant differences between treatments T1 and T3, T4, and T2 and T4, with p-values under 0.05 (Figure 13). From 16 to 30 DAS, plant height increased rapidly for all treatments without significant differences. During 31 to 60 DAS, growth slowed, and differences between treatments were not significant (Figure 14). Plant height stabilized from 61 to 75 DAS, with significant differences found between T1, T2, and T3, T4, though height remained stable (Figure 14). Overall, T4 consistently showed the highest growth rate compared to the other treatments.



Figure 13. The effect of different amounts of IWA on stem diameter over time. Data represents the mean \pm error bars of standard deviation (\pm 1) of all replicates at a particular DAS. Different lowercase letters indicate significant differences among treatments at P < 0.05 level



Figure 14. The growth curve of sweet corn in terms of stem diameter at specific DAS for each treatment

Single Fruit Weight

The study investigated how irrigation quantity (IWA) impacted sweet corn quality, focusing on Single Fruit Weight (SFW). Figure 15 shows that higher irrigation levels resulted in

significantly higher SFW, with T3 and T4 yielding the largest fruits. ANOVA revealed substantial differences among treatments (P < 3.9161E-12), with SFW values of 96.65 g, 152.87 g, 217.21 g, and 278.13 g for T1 through T4, respectively. Lower irrigation (T1 and T2) reduced ear diameter and weight due to decreased photosynthesis and assimilate production, affecting final yield. Water deficit stress was linked to poor flower development and lower yield (Sah et al., 2020).



Figure 15. The effect of different amounts of IWA on SFW right after harvesting. Data represents the mean \pm error bars of standard deviation (\pm 1) of all replicates at a particular DAS. Different lowercase letters indicate significant differences among treatments at P < 0.05 level

Kernel Moisture Content

Sweet corn growers and processors aim to achieve kernels with specific qualities, such as a tender pericarp, creamy texture, high sugar content in the endosperm, low starch content and high water content (Ha, 2017). The results of ANOVA indicated a significant effect of different irrigation water amounts (IWA) on kernel moisture content (MC), as demonstrated in Figure 16. The Tukey test revealed that both T1 and T2 were not significantly different but significantly different from T3 and T4. In contrast, T3 and T4 showed significant differences from the other treatments. T4 had the highest MC at 78.20%, followed by T3 at 76.05%, T2 at 72.29%, and T1 the lowest at 71.65%. Upon comparing means, it became apparent that grain yield showed a significant increase under optimal irrigation treatments, T3 and T4, in contrast to the suboptimal treatments, T1 and T2.



Figure 16. Different amounts of IWA affect kernel moisture content right after harvest. Data represents the mean \pm error bars of standard deviation (\pm 1) of all replicates at a particular DAS. Different lowercase letters indicate significant differences among treatments at P < 0.05 level



Figure 17. Physical appearance of corn kernel before (A) and after (B) the oven drying process

Persistent water stress caused by deficit irrigation in T1 and T2 could lead to kernel desiccation (Figure 17). Desiccation refers to the drying out of kernels due to inadequate water supply. Prolonged water stress can significantly decrease kernel moisture content, reducing kernel weight and potentially lowering overall yield (Figure 18).



Figure 18. The difference in corn cob size for each treatment (A) and desiccation of corn kernel (B) by T_1

Optimal Water Requirement

Table 3 summarizes plant growth parameters 75 days after sowing (DAS), showing significant differences in moisture content, Single Fruit Weight (SFW), stem diameter, and plant height between treatments. Table 4 indicates strong correlations among these parameters (p < 0.001).

The "Pakej Teknologi Jagung Manis" booklet recommends plant heights of 165 cm to 215 cm, which are only T3 (170.71 cm) and T4 (180 cm). None of the treatments achieved the 20 mm minimum stem diameter, though T4 (18 mm) was the closest. The stem diameter measurements at 75 DAS may differ from other studies due to varying stages or conditions. However, T4 still showed healthy growth and good yield quality, indicating minimal impact on overall performance.

Only T4 met the recommended SFW range of 250 g to 325 g, with an average of 278.13 g. T3 and T4 also met the optimal moisture content of 76%–79%, while T1 and T2 did not. Based on these results, T4 was the best irrigation practice for achieving optimal growth and quality in Malaysian sweet corn, outperforming T3 in plant height, stem diameter, SFW, and moisture content.

Treatment	Total IWA (mm)	Plant Height (cm) N = 7	Stem Diameter (mm) N = 7	SFW (g) N = 5	Moisture Content (%) N = 5
T1	140.36	$138.29 \pm 12.74 \; b$	$12.89 \pm 1.44 \ c$	$96.65 \pm 3.73 \ d$	$71.65 \pm 1.16 \text{ c}$
T2	210.50	$155.14\pm8.99\ ab$	$14.81\pm0.77\ b$	$152.87\pm9.10\ c$	$72.29\pm0.75\ c$
T3	280.67	$170.71 \pm 21.52 \text{ ab}$	$17.14\pm0.80\ a$	$217.21 \pm 19.13 \ b$	$76.05\pm0.55\ b$
T4	350.83	$180.00 \pm 17.87 \ a$	$18.73\pm1.25~a$	$278.13 \pm 34.72 \ a$	$78.20\pm0.92\ a$

 Table 3

 Average parameters growth readings for each treatment at 75 DAS

Note: Data represent the mean \pm standard deviation on four growth parameters of 7 replicates. Different lowercase letters indicate significant differences among treatments at P < 0.05 level

	Growth Parameters	SFW	Moisture Content	Plant Height	Stem Diameter
SFW	Pearson Correlation	1	0.890**	0.698**	0.891**
	Sig. (2-tailed)		0.000	0.000	0.000
	Ν	26	26	26	26
Moisture Content	Pearson Correlation	0.890**	1	0.653**	0.867**
	Sig. (2-tailed)	.000		.000	.000
	Ν	26	26	26	26
Plant Height	Pearson Correlation	0.698**	0.653**	1	0.748**
	Sig. (2-tailed)	0.000	0.000		0.000
	Ν	26	26	26	26
Stem Diameter	Pearson Correlation	0.891**	0.867**	0.748**	1
	Sig. (2-tailed)	0.000	0.000	0.000	
	Ν	26	26	26	26

Table 4						
Pearson	correlation	of	parameters	at	75	DAS

**. Correlation is significant at p-value 0.01 level (2-tailed)

Comparison with Other Studies

This study shared similarities with other studies with its aim to optimize water use in agriculture and in its use of climatic data to estimate water requirements (Table 5). Like the other studies, it evaluated different irrigation levels to determine the most effective crop growth and yield practices. However, it differed in its focus on sweet corn under local Malaysian conditions, using long-term climatic data and specific irrigation treatments. In contrast, the study by Shaw et al. (2023) covered various crops in an arid region, and Hong et al. (2022) focused on tomatoes in a greenhouse setting in China. Ray et al. (2023) offered a broader, global perspective on maize irrigation strategies, while Mirhashemi and Panahi (2021) examined maize water requirements in a specific region of Iran using environmental factors. The studies used different methods; this study employed CROPWAT software for ET_c estimation and experimental validation, while others used various models and algorithms based on their specific environmental and crop contexts. Thus, all studies aimed to improve irrigation efficiency differed in scope, methodology, and regional applicability.

Aspect	This study	Shaw et al. (2023)	Hong et al. (2022)	Ray et al. (2023)	Mirhashemi & Panahi (2021)
Objective	Determine the optimal water requirement for sweet corn using ET _c and validate it with different irrigation treatments.	Optimize furrow irrigation design for various crops in arid conditions.	Identify optimal water requirement for tomatoes in a greenhouse to improve yield and Water Use Efficiency (WUE).	Review strategies to enhance maize water productivity under different irrigation methods.	Predict maize water requirements at different growth stages under natural factors.
Water Requirement Estimation	Based on 30-year climatic data and ET _c estimated with CROPWAT V8, four irrigation treatments (50%, 75%, 100%, and 125% ET _c) were tested.	ET _c estimated with Penman-Monteith equation and CROPWAT 8.0; calculated CWR, Net Irrigation Requirement (NIR), and Gross Irrigation Requirement (GIR) for multiple crops.	Calculated using root distribution, soil moisture, and wetted percentage for five irrigation levels (60%, 80%, 100%, 120%, 140% medium irrigation quota).	Discusses water requirements for maize with furrow and drip methods; ranges from 425–789 mm (furrow) and 351–685 mm (drip).	Estimated using algorithms (C5.0, CART, CHAID, QUIST) based on factors like humidity, precipitation, air temperature, and wind speed.
Growth Parameters and Yield	Assessed plant height, stem diameter, shoot fresh weight, and kernel moisture content; T4 (125% ET ₀) optimal.	Focused on maximizing dry yield; detailed NIR values for crops including maize.	Studied tomato yield, WUE, and fruit quality; 120% Ia optimal for balancing yield and efficiency.	Discusses yield improvement under different irrigation methods; drip irrigation boosts yield by 28%.	Analyzed growth stages and natural factors affecting water requirements; key influences include precipitation, temperature, and wind speed.
Environmental and Soil Conditions	Conducted in Malaysia with data from Subang weather station; focused on local sweet corn cultivation.	Conducted in Kurnool District, India; considered various soil types and arid conditions.	Conducted in a solar greenhouse in the Taklimakan Desert, China.	It covers global conditions and discusses irrigation methods in various climates and soil types.	Conducted in the Qazvin plain, Iran; findings influenced by local natural factors.

 Table 5

 Comparison of studies on crop water requirements and irrigation practices

Sweet Corn Water Requirement: Meteorology and Growth

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Aspect	This study	Shaw et al. (2023)	Hong et al. (2022)	Ray et al. (2023)	Mirhashemi & Panahi (2021)
Methodology	ET _c estimation using CROPWAT V8; experimental validation with different irrigation treatments.	Penman-Monteith equation, CROPWAT 8.0, and FURDEV were used and compared the models for accuracy.	The TOPSIS method was used to determine optimal irrigation for yield and WUE.	Reviewed global irrigation strategies (furrow, drip, mulching) for maize.	Algorithms (C5.0, CART, CHAID, QUIST) and Apriori were used to predict water requirements and analyze association rules.
Challenges and Limitations	Specific to Malaysian conditions, it may not generalize to other climates or soils.	Tailored to arid conditions and specific soils; limited generalizability.	Results are specific to greenhouse conditions.	The broad review may lack specific details for certain regions.	Local factors influence findings and have limited broader applicability.

CONCLUSION

In conclusion, this study included a variety of activities, such as lab experiments, fieldwork, software analysis, collaboration with external agencies, and statistical data analysis, to improve the accuracy of CWR estimations for sweet corn. Using the Penman-Monteith method from FAO 56 guidelines and the CROPWAT 8 software, we calculated reference evapotranspiration (ET_o), crop evapotranspiration (ET_c), and irrigation requirements based on 30 years of climatic data from MetMalaysia. Although ETo slightly declined from March to June, it did not significantly affect ET_c due to varying crop coefficients (K_c) at different growth stages.

The total water requirement for sweet corn was estimated at 251.1 mm/day or 360.86 mm/season, assuming a 70% irrigation efficiency. A field study at the Greenhouse, Ladang 15, Faculty of Agriculture, UPM, tested different irrigation levels (50%, 75%, 100%, and 125% of ET_c) to validate practical irrigation management strategies that utilize the refined CWR estimations through the experimental site. Key growth parameters such as plant height, stem diameter, single fruit weight, and kernel moisture content were recorded.

Results showed that plants receiving irrigation water application T4 at 125% ET_c had better growth and higher survival rates compared to other treatments. Statistical analysis confirmed that higher irrigation levels significantly improved plant growth (P < 0.05). It was concluded that the estimated irrigation based on T3 at 100% ET_c was insufficient, and T4 at 125% ET_c was most suitable for optimal sweet corn growth in Malaysia. The study demonstrated that optimizing irrigation to 125% of the estimated crop water requirement (based on ET_c) significantly improved sweet corn growth and survival, validating refined CWR estimations and highlighting the necessity of adjusting irrigation strategies to achieve optimal crop productivity.

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