



Optimizing water management in greenhouse farming through an IoT-enabled monitoring system

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Abstract

Understanding the crop growth and yield response to variable irrigation and the relationship between crop eco-physiological and morphological parameters is critical for identifying a balanced irrigation management strategy and developing decision support systems for early detection and information for on-ground decisions. The Internet of Things model was constructed to be used in the permanent and continuous monitoring of plants through various measurements. The present study aimed to optimize water use, monitor environmental factors, and improve crop yield. The field experiment was conducted in a greenhouse at SEKEM Company for Biodynamic Agriculture in Egypt during the winter season of 2022–2023. Green bean plants (*Phaseolus vulgaris* L.) were cultivated under two irrigation systems: surface drip irrigation (SDI) and subsurface drip irrigation (SSDI), with three irrigation levels of 100%, 80%, and 60% of the crop water requirements (CWR). This resulted in a total of six experimental treatments (T): T1, T3, and T5 for SDI; and T2, T4, and T6 for SSDI. An Internet of Things (IoT) unit equipped with sensors was installed to monitor air temperature, air humidity, and soil moisture, enabling the calculation of vapor pressure deficit (VPD). Data were collected daily throughout the growth stages. IoT unit with sensors were installed to monitor air temperature, air humidity, and soil moisture, enabling vapor pressure deficit (VPD) calculations. The measurements were collected daily during the growth stages. The field trial results demonstrated that SSDI at 100% CWR (T2) was recorded the lowest VPD values (1.34, 0.67, and 2.10 kPa) during development, Mid, and Late stage, respectively, while SDI at 60% CWR (T5) recorded the highest (1.77, 1.19, and 2.72 kPa) during development, Mid, and Late stage, respectively. Canopy temperatures were lower under SSDI (T2) compared to SDI (T5). Green bean yield significantly varied between irrigation methods. SDI yield ranged from 25.425 to 28.719 t ha⁻¹, with the highest (28.719 t ha⁻¹) at 80% CWR (T3), while the SSDI yield ranged from 24.390 to 33.614 t ha⁻¹, with the maximum 33.614 t ha⁻¹ recorded under 80% CWR (T4). Water productivity (WP) varied significantly, from 7.66 to 15.73 kg m⁻³. The highest WP (15.73 kg m⁻³) was recorded under SSDI at 60% CWR (T6), while the lowest (7.66 kg m⁻³) occurred under SSDI at 100% CWR (T2). The study underscores IoT-based precision irrigation's potential to maximize yields and enhance water efficiency, with SSDI proving more efficient at lower irrigation levels.

Keywords IoT · Water management · Vapor pressure deficit (VPD) · Canopy temperature (CT) · Water productivity (WP) · Drip irrigation

1 Introduction

For arid and semi-arid regions, irrigation of agriculture accounts for a significant portion of freshwater consumption (Roldán-Cañas and Moreno-Pérez 2021). Effective irrigation methods are crucial for meeting plant water needs while preventing excessive evaporation, soil dryness, and water shortages. Conventional irrigation methods often result in inefficient water distribution, leading to a reduced agricultural productivity (Inayah et al. 2025). Food and

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Agriculture Organization (FAO) forecasts that irrigated food production will rise by over 50 % by the year 2050. However, achieving this increase will require a 10 % rise in agricultural water withdrawal, contingent upon improvements in water productivity (FAO 2020). Precision irrigation scheduling focuses on optimizing water use for each plant by delivering the required amount at the right time and location. This approach aims to compensate for water losses due to evapotranspiration, erosion, or deep percolation, while simultaneously preventing both over-irrigation and under-irrigation (Benyezza et al. 2018; Gu et al. 2020). Effective water scheduling not only ensures a sufficient water supply but also aids farmers in optimizing irrigation and fertilization management, thereby reducing production costs and enhancing economic benefits. Effective irrigation management, achieved through precise monitoring and optimal control, can lead to significant water savings while also reducing indirect costs associated with energy consumption, such as electricity or fossil fuels used for pumping. This approach enhances overall cost-effectiveness in agricultural operations (Togneri et al. 2019; Cáceres et al. 2021). The Internet of Things (IoT) has widespread applications across various sectors, ranging from automation industries to smart agriculture. It is a cutting-edge technology that integrates a variety of sensors and electronic devices, all interconnected through the internet, enabling efficient data collection and system automation in diverse fields (Gupta et al. 2021, 2019). Advancements in technology and the development of affordable sensors have enabled precision irrigation systems to monitor soil, plant, and atmospheric moisture levels. These systems provide irrigators with real-time field data, allowing them to apply water precisely when and where it is needed, optimizing irrigation efficiency (Abioye et al. 2022). Crop evapotranspiration (ET_C) is a critical factor for optimizing irrigation water productivity and developing effective irrigation schedules in agricultural water management, particularly in greenhouse environments where irrigation is the primary source of water. ET_C variations are significantly impacted by the amount of irrigation water applied, especially when different irrigation levels are used (Hooshmand et al. 2019).

Greenhouse-grown vegetable crops experience lower seasonal crop evapotranspiration (ET_C) compared to the same crops irrigated in outdoor conditions due to the reduced evaporative demand within the greenhouse. This decrease is attributed to factors such as lower solar radiation, averaging 40 % less than outdoor levels, and significantly reduced wind speeds (0.1–0.3 m s⁻¹ or less). As a result, the evaporative demand inside the greenhouse can be as low as 60 % of what is observed in outdoor environments (Fernández et al. 2010).

The primary factor controlling water uptake in greenhouse environments, which subsequently influences other physiological processes such as pollination, growth, and

yield, is the air water vapor pressure deficit (VPD). VPD serves as the driving force for water movement between the roots and leaves. Furthermore, VPD provides a more precise representation of plant stress by considering both temperature and relative humidity (RH) measurements (Shamshiri et al. 2018). The vapor pressure deficit (VPD) is influenced by both temperature and relative air humidity. Various evaporative systems are employed in different contexts, with most being operated in a simple on/off manner, which can lead to fluctuations in air humidity due to their binary control. As a result, high VPD levels may occur during the day, even in controlled greenhouse environments (Zhang et al. 2017; Inoue et al. 2021). Humidity alone does not offer sufficient information about plant transpiration and is not an accurate indicator of vapor pressure stress on plants.

Canopy temperature has been measured since the 1980s using simple radiometers for irrigation scheduling and assessing plant traits (Rebetzke et al. 2012). It is affected by transpiration and environmental factors, prompting the development of normalization methods using reference surfaces (Maes et al. 2016). While thermal imaging is growing, fixed thermal sensors provide more consistent and reliable data for plant breeding and irrigation management (Rebetzke et al. 2016).

In arid regions where water is scarce, smart technologies are essential to enhance irrigation efficiency and crop productivity. Drip irrigation is globally acknowledged as a highly efficient, water-saving technology, particularly in arid and semi-arid regions. It not only enhances crop yield and quality but also improves water and fertilizer productivity (Wang et al. 2021). Subsurface drip irrigation (SSDI), an advanced form of surface drip irrigation (SDI), delivers water and liquid fertilizer directly to the root zone within the plough layer through a network of emitters. Subsurface irrigation systems help conserve water by minimizing evaporation and reducing water loss (Zheng et al. 2025; Wang et al. 2022). Recent studies have shown that SSDI significantly improves crop growth by minimizing deep percolation, reducing soil surface evaporation, and suppressing weed growth, thereby increasing crop water productivity (Yao et al. 2021). However, traditional subsurface systems often require manual monitoring and may lack precision due to their hidden layout. Integrating smart SSDI systems with Internet of Things (IoT) and cloud technologies enables real-time monitoring and automated control, which improves water use efficiency and reduces labor demands (Mohammed et al. 2021; Ndunagu et al. 2022). Furthermore, IoT supports broader agricultural applications such as water reuse, pollution control, and livestock management by enabling data-driven decisions (Zia 2022). These advancements are particularly crucial in regions with limited irrigation infrastructure, where optimizing crop water productivity is vital (Duguma and Bai 2024).

Green bean (*Phaseolus vulgaris* L.), a member of the Fabaceae family, is widely cultivated across the world due to its high nutritional value (Uebersax et al. 2023; Chaurasia 2020). It is a popular yet water-intensive vegetable crop, known for its sensitivity to both drought and over-irrigation (Uebersax et al. 2023). Higher temperatures lead to increased evapotranspiration and plant water demand, which can negatively affect food production, particularly for water-sensitive crops like green beans. In 2020, global production of green beans reached approximately 4,310,733 metric tons, with Egypt contributing 265,000 tons, ranking 7th worldwide (Sadok et al. 2021; El Haddad et al. 2021).

The objectives of this study were: (1) To develop an IoT-based system for continuous monitoring of soil moisture, air temperature, humidity, vapor pressure deficit (VPD), and plant canopy temperature in a greenhouse environment. (2) To optimize irrigation scheduling based on real-time data to minimize water waste. (3) To improve crop productivity and water productivity through data-driven irrigation decisions. (4) To evaluate the impact of IoT-enabled irrigation on water use efficiency in subsurface drip irrigation systems.

2 Materials and methods

2.1 Study area and experimental design

A field experiment was carried out at the SEKEM Company for Biodynamic Agriculture, situated in Belbeis City, Sharkia Governorate, Egypt. The experimental site is geographically located at 30.416667° N latitude and 31.639833° E longitude, with an elevation of approximately 9.6 m above sea level. During the crop growing season, the meteorological conditions outside the greenhouse showed considerable variation. The recorded daily maximum air temperatures ranged between 14.9 °C and 36.01 °C, while the minimum temperatures fluctuated from 4.17 °C to 19.0 °C. Relative humidity levels also varied significantly during the season, ranging from 24 to 80%, reflecting the arid to semi-arid nature of the local climate. These data were obtained from the Central Laboratory for Agricultural Climate (CLAC), which operates under the Agricultural Research Center (ARC) of the Ministry of Agriculture, Giza, Egypt. It is worth noting that no rainfall occurred at the experimental site during the growing season.

Green beans (*Phaseolus vulgaris* L.) were chosen for this investigation due to their high nutritional value, global economic importance, and sensitivity to water stress (Riyaz et al. 2024). As a widely cultivated, water-intensive crop, green beans serve as an ideal model for evaluating the effects of different irrigation strategies on yield and water use efficiency (Dewedar et al. 2021; Saleh et al. 2018; Sezen et al.

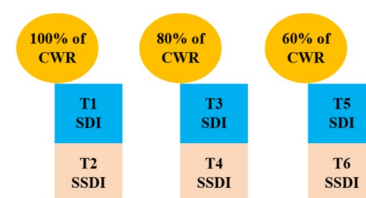
2005). Their responsiveness to both drought and over-irrigation makes them particularly suitable for studying the impact of optimized irrigation practices under arid and semi-arid conditions (Palumbo et al. 2021).

Green bean (*Phaseolus vulgaris* L.) seedlings were cultivated in a greenhouse during the winter season of 2022–2023, from October 2022 to March 2023. The experiment followed a split-plot design with three replicates, covering a total area of 23 m × 15.60 m. The experimental field was divided into three main plots, each measuring 23 m × 5.20 m, assigned to different irrigation levels: 100%, 80%, and 60% of the crop water requirement (CWR) (Fig. 1). As shown in Fig. 2, each main plot was further divided into two subplots, each measuring 23 m × 2.60 m. One subplot was designated for surface drip irrigation (SDI), and the other for subsurface drip irrigation (SSDI). Each subplot contained three rows of green bean plants, spaced 0.30 m apart. Drippers were installed along the drip lines at the same spacing, aligned directly with the plants. The drippers had a discharge rate of 3.4 L h⁻¹. For the SSDI treatment, drip lines were buried at a depth of 15 cm.

It is worth noting that randomization was not implemented in this experiment due to the fixed design of the irrigation system, which prevented spatial rearrangement of treatments. Each line was pre-installed to deliver specific water levels (100%, 80%, or 60% of CWR) via SDI or SSDI. Redesigning the system to allow randomization was not feasible due to technical and logistical limitations. To reduce spatial variability effects, plots were placed under uniform soil and topographic conditions, consistent agronomic practices were applied, and measurements were replicated within treatments. Although full randomization was not possible, field variability was controlled as much as possible within the setup constraints.

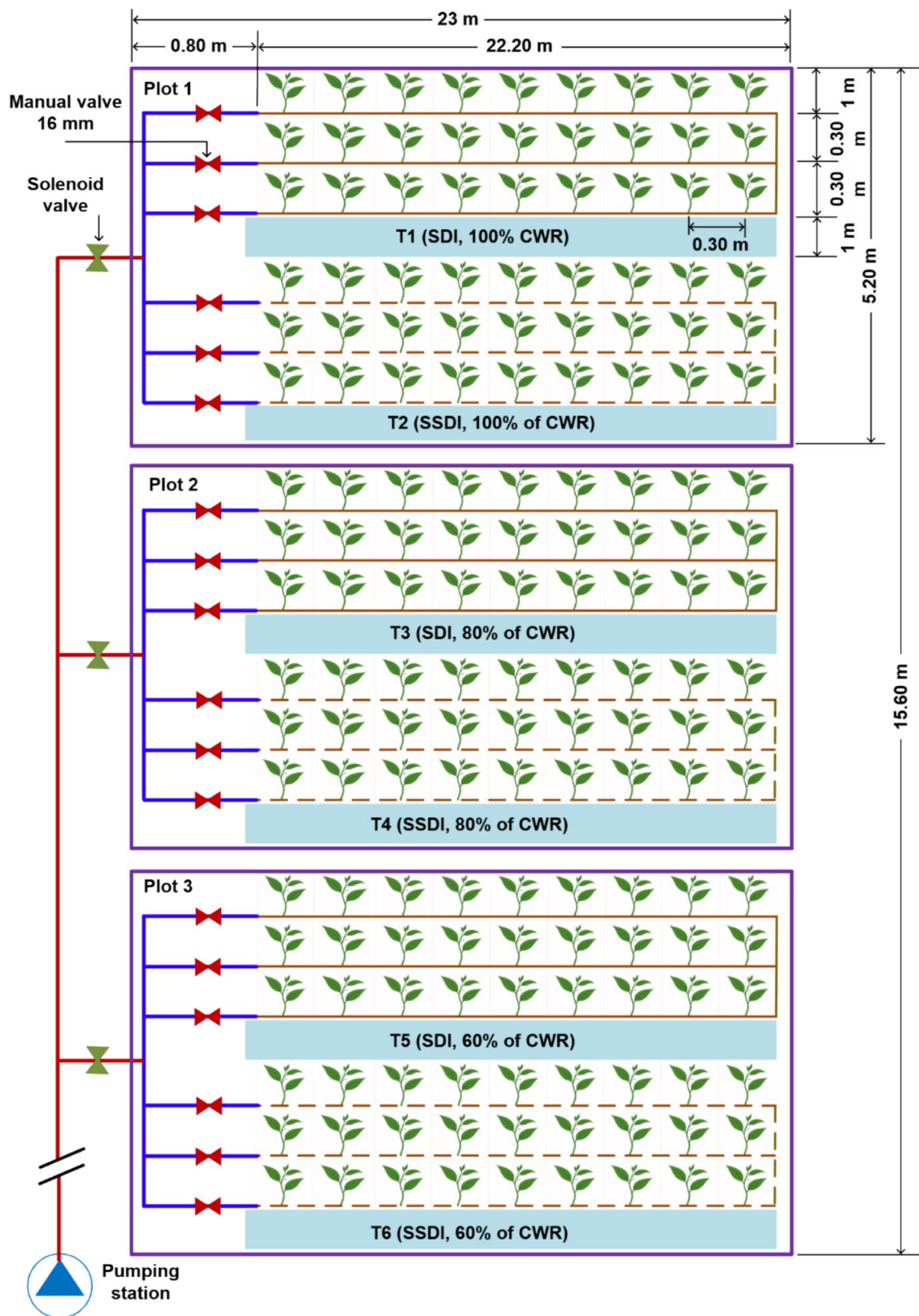
2.2 IoT-based monitoring system

The IoT-based monitoring system in the current study is distinguished by its integration of real-time data acquisition with remote accessibility and automation tailored specifically for managing drip irrigation under varying



CWR: Crop water requirements, T: Treatment, SDI: Surface drip irrigation, and SSDI: Subsurface drip irrigation.

Fig. 1 Schematic diagram of the experimental treatments



T: Treatment, CWR: Crop water requirements, SDI: Surface drip irrigation, and SSDI: Subsurface drip irrigation.

Fig. 2 Layout of the experimental field design and treatments setting

water regimes. Unlike many previous studies that focused on either data logging or limited sensor types, our system combines soil moisture, temperature, and environmental sensors with cloud-based data processing and user-friendly interfaces. This enhances precision irrigation decision-making and resource efficiency. The significance of this system lies in its ability to support timely, data-driven interventions, ultimately improving water use efficiency and crop productivity under field conditions.

The Internet of Things (IoT) system was used for the continuous and permanent monitoring of plants through various measurements, including air temperature, air humidity, and soil moisture. Two units were used in the experiment: the first unit was an IoT data collection unit, and the second was a specialized irrigation control unit. These units aimed to optimize water management for green bean cultivation. By leveraging the combined capabilities of cloud computing and IoT technology, the system sought to achieve precise control of irrigation systems,

ensuring efficient water utilization and maximizing green bean yield.

The system was used to collect data from the experimental field and transmit it via Wi-Fi to the user every 15 min. The system consists of a microcontroller (ESP32-S board), infrared thermometer (MLX90614), digital-output relative humidity and temperature sensor/module (DHT22), digital thermometer (DS18B20), capacitive soil moisture sensor, two-channel relay, micro-SD card reader module, 5 V DC fan, waterproof project box, and power supply, as shown in Fig. 3.

2.3 Data collection and analysis

Soil samples were collected from each profile at three depths: 0–15 cm, 15–30 cm, and 30–45 cm. After air-drying, the samples were sieved through a 2 mm mesh to obtain fine soil for analysis. Soil texture analysis revealed that the soil at the experimental site is classified as loamy sand. The

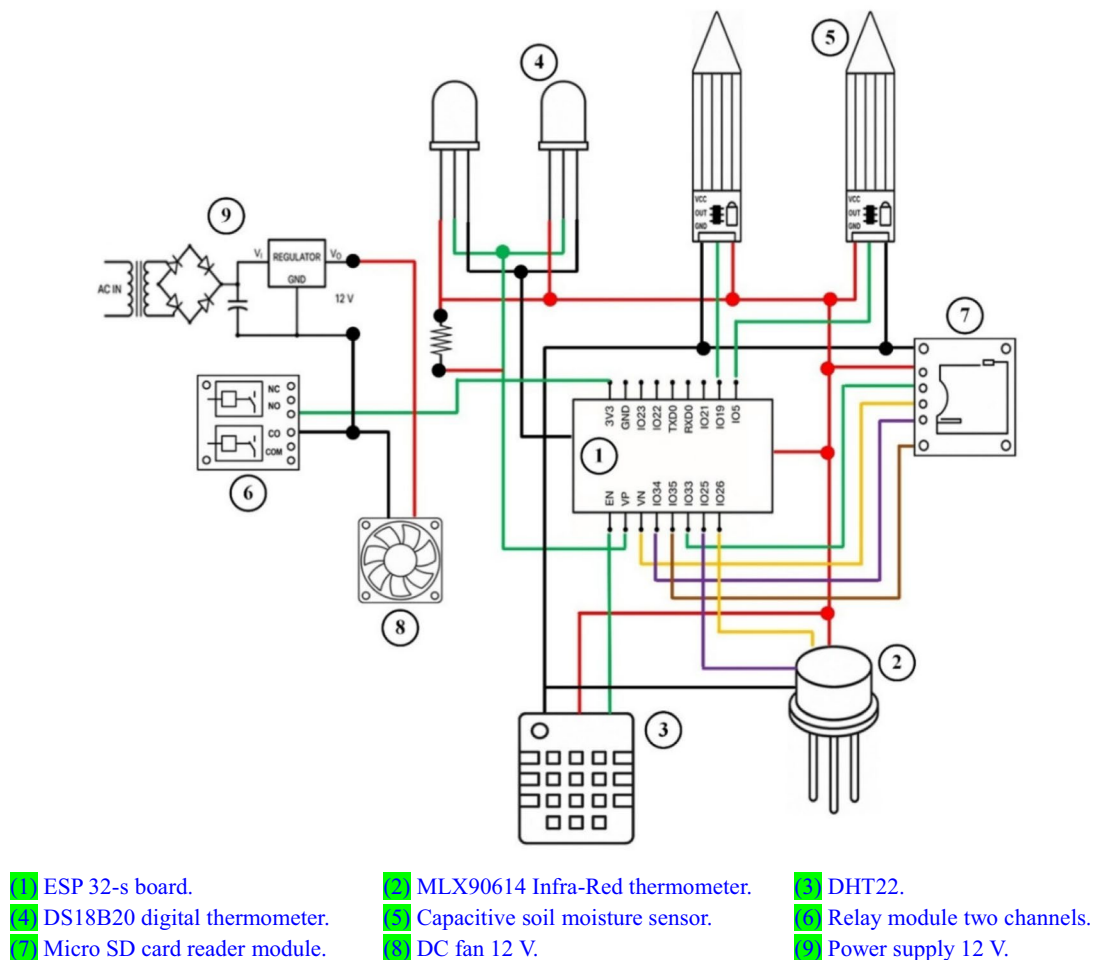


Fig. 3 The schematic and detailed diagram of system

Table 1 Soil physical analysis of experimental site

Soil depth (cm)	Soil particles percentages (%)			Texture	Bulk Density (g cm ⁻³)	Field capacity (%)	Permanent wilting point (%)	Available Water (%)
	Sand (%)	Silt (%)	Clay (%)					
0–15	84.72	7.17	8.11	Loamy	1.54	17.53	6.81	10.72
15–30	85.24	6.81	7.95	Sand	1.56	17.28	6.77	10.51
30–45	86.26	6.51	7.23		1.59	17.12	6.63	10.49
Mean	85.41	6.83	7.76		1.56	17.31	6.74	10.57

soil's physical properties are summarized in Table 1. These analyses were performed at the Soil, Water and Environment Research Institute, Agricultural Research Center, Ministry of Agriculture, located in Giza, Egypt.

The air temperature around the plants was measured using an MLX90614 infrared thermometer, while relative humidity (RH%) was recorded every 15 min using DHT22 sensors. The average vapor pressure deficit (VPD), expressed in kPa, was calculated under different irrigation levels for two irrigation systems; surface drip irrigation (SDI) and subsurface drip irrigation (SSDI). Measurements were taken at six mid-day time points (10:00 AM, 11:00 AM, 12:00 PM, 1:00 PM, 2:00 PM, and 3:00 PM), which typically correspond to the highest daily temperatures. The vapor pressure deficit (VPD) is commonly measured between 10:00 AM and 3:00 PM, as this period aligns with the peak of plant physiological activity and maximum evapotranspiration rates. The rationale for this timing is supported by the following factors:

Peak Daily Temperatures: During this time window, air temperatures typically reach their daily maximum, directly affecting the saturated vapor pressure (SVP). As temperature increases, the air's capacity to hold water vapor also increases, which raises VPD particularly when relative humidity is low. This relationship is critical in understanding atmospheric demand for water and its impact on plant water loss (Allen et al. 1998; Monteith and Unsworth 2013).

Maximum Photosynthetic and Transpirational Activity: Plants generally open their stomata during daylight hours to take in CO₂ for photosynthesis, with the highest stomatal conductance and transpiration typically occurring between late morning and early afternoon. Elevated VPD during this period indicates drier air, which enhances transpiration and can increase the risk of plant water stress if the deficit becomes too large (Jones 2014; Oren et al. 1999; Sinclair and Ludlow 1986).

Mid-day Decline in Relative Humidity (RH): Relative humidity tends to decrease around midday due to rising temperatures, even if the actual moisture content of the

air remains constant. This inverse relationship between temperature and RH contributes to a higher VPD during this period, making it a sensitive time frame for detecting crop stress and guiding irrigation decisions (Tardieu and Simonneau 1998; McNaughton and Jarvis 1991).

The average VPD was determined for three crop growth stages: development, mid-season, and harvest. Irrigation treatments were applied starting 20 days after planting and continued until the harvest stage of winter green beans grown under the respective irrigation regimes.

2.4 Determination of crop evapotranspiration (ET_o)

Daily crop evapotranspiration (ET_C) was computed using Eq. (1), following the guidelines provided by Allen et al. (1998). The reference evapotranspiration (ET_o) was estimated using the CropWat 8 software, which applies the FAO Penman–Monteith equation as in Eq. 2. This approach considers key climatic variables such as air temperature, relative humidity, wind speed, and solar radiation to calculate ET_o accurately. To convert ET_o to ET_C, appropriate crop coefficient (K_C) values were applied, which vary depending on the crop type and its developmental stage.

For green bean (*Phaseolus vulgaris* L.), the growing period was divided into four standard stages as defined by Allen et al. (1998): the initial stage, crop development stage, mid-season stage, and late-season stage. The crop coefficients assigned to each stage were 0.50 for the initial stage, 1.05 for both the development and mid-season stages, and 0.90 for the late-season stage. These K_C values were used to adjust ET_o and obtain the actual ET_C for each day of the growing season. The duration of irrigation required to meet ET_C was then determined using Eq. (3), which factored in the flow rate of the irrigation system and the irrigated area.

$$ET_C = ET_O \times K_C \quad (1)$$

$$ET_O = \frac{0.408 \Delta (R_n - G) + \gamma \frac{900}{T+273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \quad (2)$$

$$T_i = \frac{D_g \times A \times 60}{Q \times 1000} \quad (3)$$

where, ET_C : is the crop evapotranspiration in (mm day^{-1}), ET_O : is the reference crop evapotranspiration in (mm day^{-1}), K_C : is the crop coefficient, R_n : is the net radiation at the crop surface in (MJ m^{-2} per day), G : is the soil heat flux density in (MJ m^{-2} per day), T : is the mean daily air temperature at 2 m height ($^{\circ}\text{C}$), u_2 : is the wind speed at 2 m height (m s^{-1}), e_s : is the mean daily saturation vapor pressure in (kPa), e_a : is the actual vapor pressure in (kPa), $e_s - e_a$: is the saturation vapor pressure deficit in (kPa), Δ : is the slope of saturation vapor pressure curve at temperature T in ($\text{kPa } ^{\circ}\text{C}^{-1}$), γ : is the psychrometric constant in ($\text{kPa } ^{\circ}\text{C}^{-1}$); T_i : is the time of irrigation in (min), D_g : is the gross water application depth in (mm), A : is the irrigated area in (m^2), and Q : is the total discharge rate of the system in (m^3h^{-1}).

2.5 Calculation of vapor pressure deficit (VPD)

Vapor pressure deficit (VPD) is determined by subtracting the actual vapor pressure (e_a) from the saturation vapor pressure (e_s) as shown in Eq. (4).

$$\text{VPD} = (e_s - e_a) \quad (4)$$

The e_s at a given temperature is calculated using Eq. (5). The daily mean, e_s , is estimated by either averaging the saturation vapor pressures at the maximum and minimum air temperatures, $e^0(T_{\max})$ and $e^0(T_{\min})$, respectively, as shown in Eq. (6), or by using the mean air temperature (T_{mean}) to determine $e^0(T_{\text{mean}})$, as in Eq. (7) (Waller and Yitayew 2016; Hoffman et al. 2007; Allen et al. 1998).

$$e^0(T) = 0.6108 \exp \left[\frac{17.27 T}{T + 237.3} \right] \quad (5)$$

$$e_s = \frac{[e^0(T_{\max}) + e^0(T_{\min})]}{2} \quad (6)$$

$$e_s = e^0(T_{\text{mean}}) \quad (7)$$

where, $e^0(T)$: is the saturation vapor pressure in (kPa) at air temperature in ($^{\circ}\text{C}$), T : is the mean daily air temperature at 2 m height in ($^{\circ}\text{C}$), $e^0(T_{\max})$ and $e^0(T_{\min})$ are the saturation vapor pressure in (kPa) at maximum and minimum temperature of air in ($^{\circ}\text{C}$) respectively, and $e^0(T_{\text{mean}})$: is the saturation vapor pressure in (kPa) at daily mean air temperature in ($^{\circ}\text{C}$)

The actual vapor pressure (e_a) is calculated using one or more of the following: relative humidity and air temperature (Allen et al. 1998). The standard methods for determining e_a are provided in Eqs. (8) – (12):

$$e_a = \frac{e^0(T_{\min}) \frac{RH_{\max}}{100} + e^0(T_{\max}) \frac{RH_{\min}}{100}}{2} \quad (8)$$

$$e_a = e^0(T_{\min}) \frac{RH_{\max}}{100} \quad (9)$$

$$e_a = e^0(T_{\max}) \frac{RH_{\min}}{100} \quad (10)$$

$$e_a = \frac{RH_{\min}}{100} \left[\frac{e^0(T_{\max}) + e^0(T_{\min})}{2} \right] \quad (11)$$

$$e_a = 0.6108 \exp \left[\frac{17.27 T_{\min}}{T_{\min} + 237.3} \right] \quad (12)$$

where, e_a : is the actual vapor pressure in (kPa); $RH_{\max}$ and $RH_{\min}$: are the maximum and minimum relative humidity in percent (%) respectively.

2.6 Water productivity (WP)

Water Productivity (WP), also referred to as Irrigation Water Use Efficiency (IWUE), represents the amount of actual yield produced in kilograms produced per unit of irrigation water applied in cubic meters, regardless of whether the water is fully consumed by the crop through evapotranspiration. Unlike Water Use Efficiency (WUE) which measures how effectively a plant physiologically utilizes water, WP provides a broader evaluation of the overall performance of the irrigation system. It accounts not only for the water absorbed by the plant but also for all potential losses, including surface evaporation, deep percolation beyond the root zone, and surface runoff (Molden et al. 2010). In this study, WP was calculated using the commonly applied Eq. (13) (Elsadek et al. 2023).

$$\text{WP} = \frac{\text{Actual yield produced (Y)}}{\text{Total water applied (TWA)}} \quad (13)$$

where, WP: is the water productivity in (kg m^{-3}), Y : is actual yield produced in (kg ha^{-1}), and TWA: is the total seasonal water applied to the field in (m^3ha^{-1}).

2.7 Statistical analysis

The results of each replicate sample were reported as the average. Significant differences between treatments were determined by AVOVA and Tukey's HSD (Honestly Significant Difference) test ($p < 0.05$) followed by LSD (the least significant difference) test using IBM SPSS Statistics

20.0 software. Microsoft Excel was used to create and edit all figures.

3 Results

3.1 Effect of treatments on the vapor pressure deficit (VPD)

Figure 4 shows that differences in applied irrigation water resulted in variations in vapor pressure deficit over time. The lowest vapor pressure deficit values of 1.09, 1.15, 1.18, 1.21, 1.32, and 1.43 kPa were observed under treatments T2, T1, T4, T3, T6, and T5, respectively, at 10 AM. The highest vapor pressure deficit values of 1.45, 1.56, 1.63, 1.71, 1.83, and 2.01 kPa were observed under treatments T2, T1, T4, T3, T6, and T5, respectively, at 1 PM. The mean air temperature in the greenhouse was recorded as 22.18 °C at 10 AM and 26.23 °C at 1 PM. The mean relative humidity (RH) in the greenhouse was 53.04 % at 10 AM and 42.96 % at 1 PM.

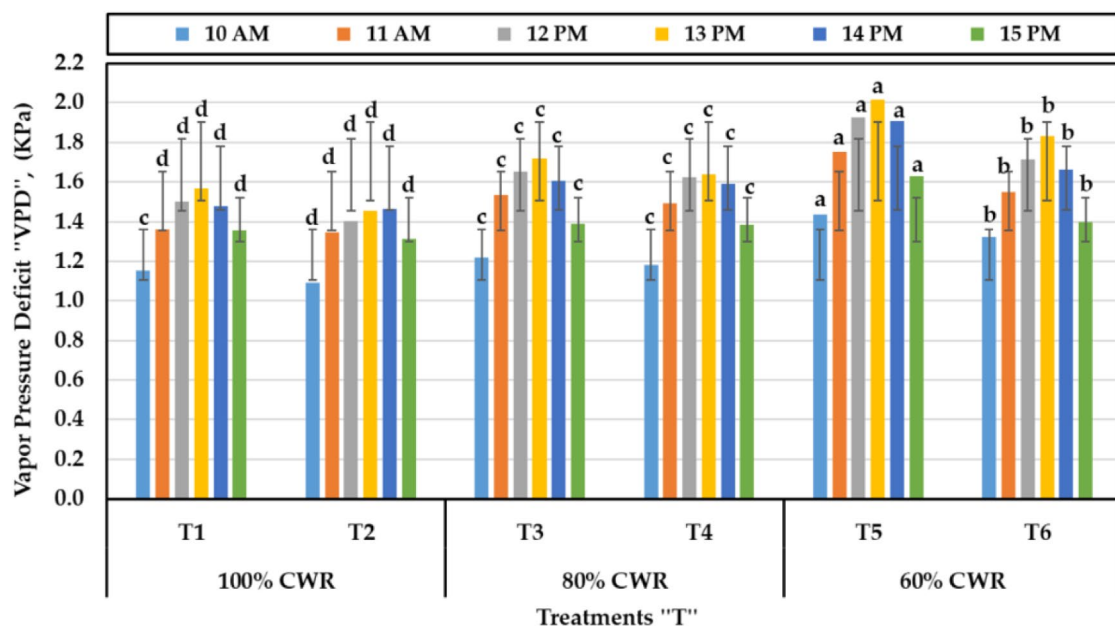
The differences in water treatments also led to variations in the mean vapor pressure deficit recorded during the development stage. The lowest mean vapor pressure deficit of 1.34 kPa was observed under the subsurface drip irrigation treatment with 100 % of the water requirement (T2), while the highest mean vapor pressure deficit of 1.77 kPa was observed under the surface drip irrigation treatment with 60 % of the water requirement (T5). The mean air

temperature in the greenhouse was 25.09 °C, and the mean RH was 46.12 %.

Figure 5 shows that differences in applied irrigation water resulted in variations in vapor pressure deficit over time. The lowest vapor pressure deficit values of 0.405, 0.427, 0.525, 0.595, 0.647, and 0.684 kPa were observed under treatments T2, T1, T4, T3, T6, and T5, respectively, at 10 AM. The highest vapor pressure deficit values of 0.834, 0.835, 0.860, 1.052, 1.44, and 1.466 kPa were observed under treatments T2, T1, T4, T3, T6, and T5, respectively, at 1 PM. The mean air temperature in the greenhouse was recorded as 18.86°C at 10 AM and 27.01°C at 1 PM. The mean relative humidity (RH) in the greenhouse was 71.38 % at 10 AM and 58.84 % at 1 PM.

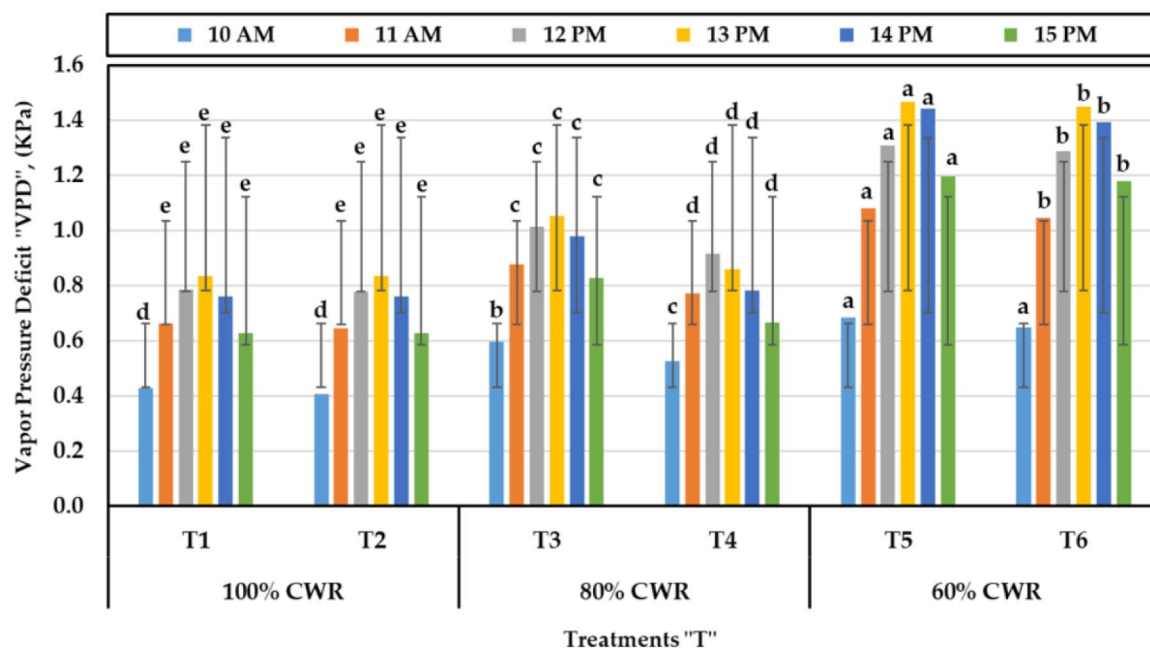
Differences in applied irrigation water also led to variations in the mean vapor pressure deficit recorded during mid-stage. The lowest mean vapor pressure deficit of 0.67 kPa was observed under the subsurface drip irrigation treatment with 100 % of the water requirement (T2), while the highest mean vapor pressure deficit of 1.19 kPa was observed under the surface drip irrigation treatment with 60 % of the water requirement (T5). The mean air temperature in the greenhouse was 24.85 °C, and the mean RH was 62.76 %.

Figure 6 shows that differences in applied irrigation water resulted in variations in vapor pressure deficit over time. The lowest vapor pressure deficit values of 1.56, 1.59, 1.81, 1.84, 1.93, and 2.06 kPa were observed under treatments T2, T1, T4, T3, T6, and T5, respectively, at 10



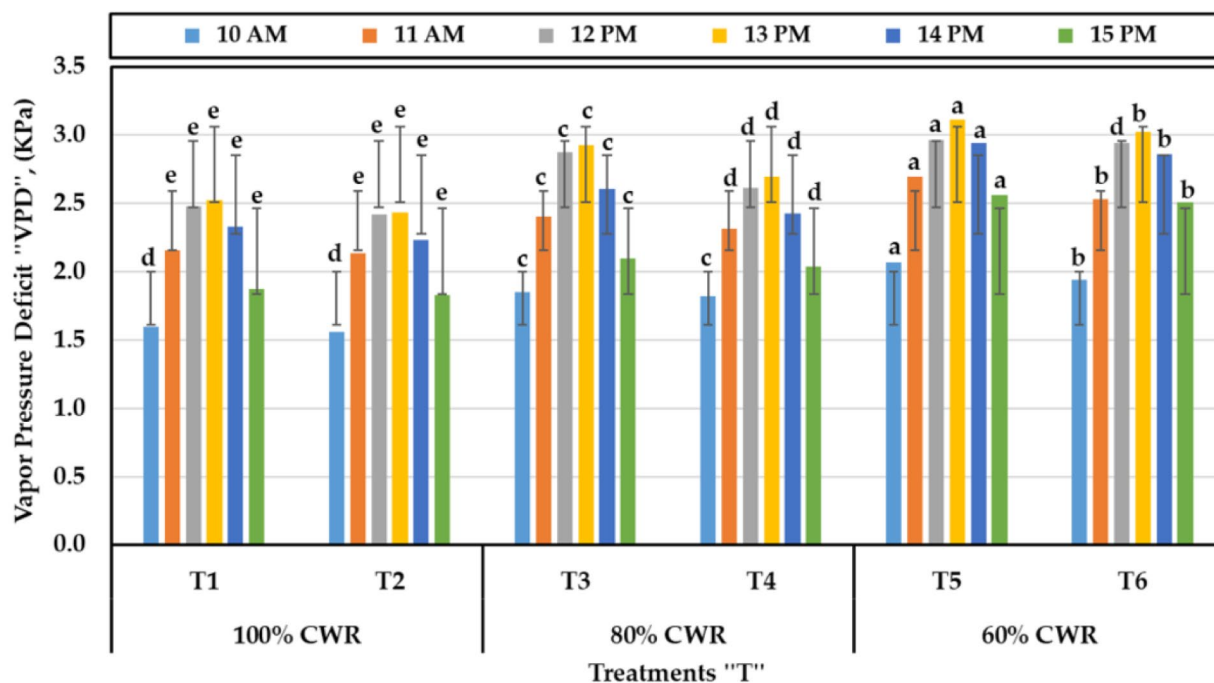
VPD: Vapor pressure deficit, T: Treatment, CWR: Crop water requirements.

Fig. 4 Comparison of average VPD (KPa) under different applied irrigation water for (SDI) and (SSDI) systems through the development stage. Differences between parameters marked with different letters are statistically significant at the $P < 0.05$ level



VPD: Vapor pressure deficit, T: Treatment, CWR: Crop water requirements.

Fig. 5 Comparison of average VPD (KPa) under different applied irrigation water for (SDI). and (SSDI) systems through the Mid stage. Differences between parameters marked with different letters are statistically significant at the $P < 0.05$ level



VPD: Vapor pressure deficit, T: Treatment, CWR: Crop water requirements.

Fig. 6 Comparison of average VPD (KPa) under different applied irrigation water for (SDI). and (SSDI) systems through the Late stage. Differences between parameters marked with different letters are statistically significant at the $P < 0.05$ level

AM. The highest vapor pressure deficit values of 2.43, 2.52, 2.69, 2.92, 3.02, and 3.11 kPa were observed under treatments T2, T1, T4, T3, T6, and T5, respectively, at 1 PM. The mean air temperature in the greenhouse was recorded as 25.55 °C at 10 AM and 32.86 °C at 1 PM. The mean relative humidity (RH) in the greenhouse was 51.06 % at 10 AM and 38.10 % at 1 PM.

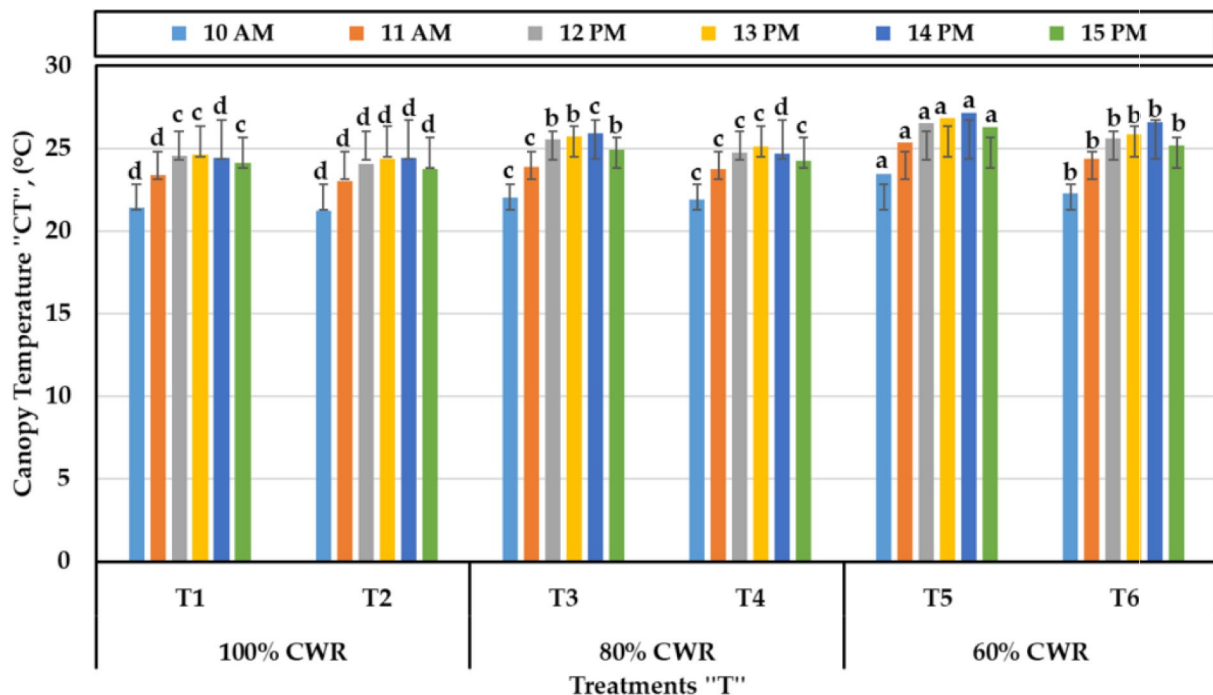
Differences in applied irrigation water also led to variations in the mean vapor pressure deficit recorded during the late stage. The lowest mean vapor pressure deficit of 2.10 kPa was observed under the subsurface drip irrigation treatment with 100 % of the water requirement (T2), while the highest mean vapor pressure deficit of 2.72 kPa was observed under the surface drip irrigation treatment with 60 % of the water requirement (T5). The mean air temperature in the greenhouse was 30.62 °C, and the mean RH was 42.59 %.

The results of statical analysis showed that T5 (60% of CWR) consistently has the highest VPD and is significantly different from other treatments. T6 (60% of CWR) is intermediate and significantly different from T5 and lower treatments. T3, T4, T1, T2 overlap in significance, with T2 (100% of CWR) generally having the lowest VPD.

3.2 Effect of treatments on the canopy temperature

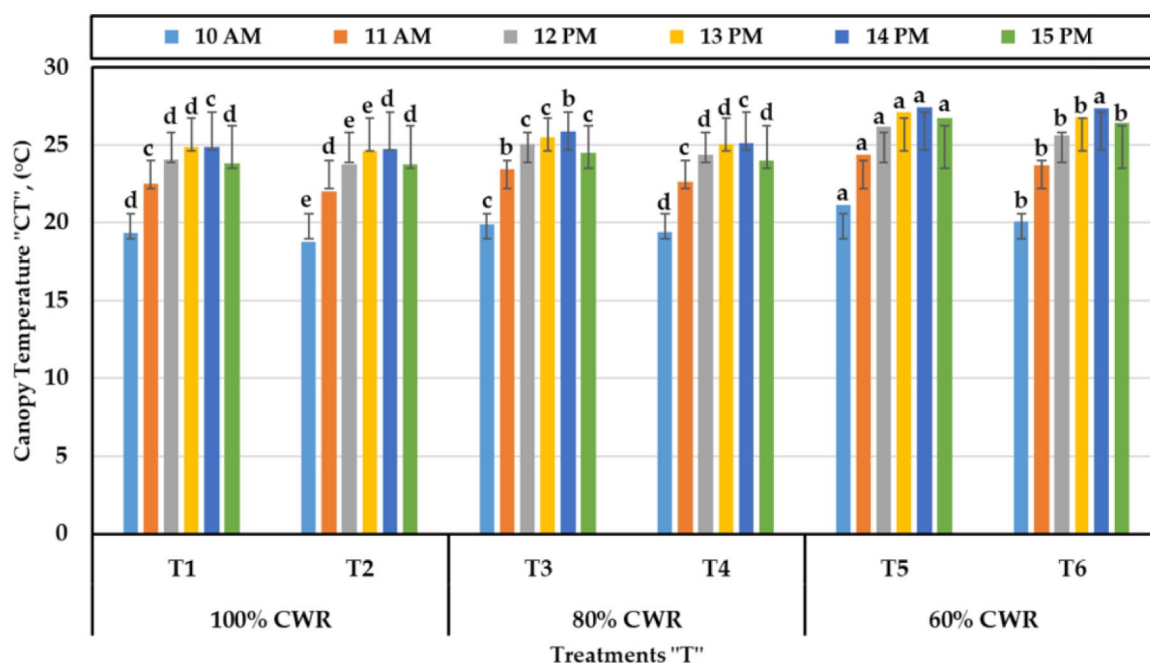
The canopy temperature is an important parameter that reflects the energy balance of plants and is influenced by both environmental and plant factors. It serves as a valuable tool for assessing the water status of plants and plays a key role in determining plant water stress.

Mean canopy temperatures were measured using an IoT system at different plant stages, starting 20 days after planting and continuing until harvest, for winter green beans grown under various irrigation treatments. The measurements were taken using MLX90614 infrared sensors every 15 min. Figures 7, 8, and 9 present the average canopy temperature values (°C) under various irrigation treatments for two irrigation systems: surface drip irrigation (SDI) and subsurface drip irrigation (SSDI). The measurements were recorded at six different times: 10 AM, 11 AM, 12 PM, 1 PM, 2 PM, and 3 PM, during midday. The average canopy temperature was recorded for three stages of crop growth: development, mid-season, and harvest. Plant canopy temperature was closely linked to the volume of water applied in both full and deficit irrigation treatments, as well as to the type of irrigation system employed.



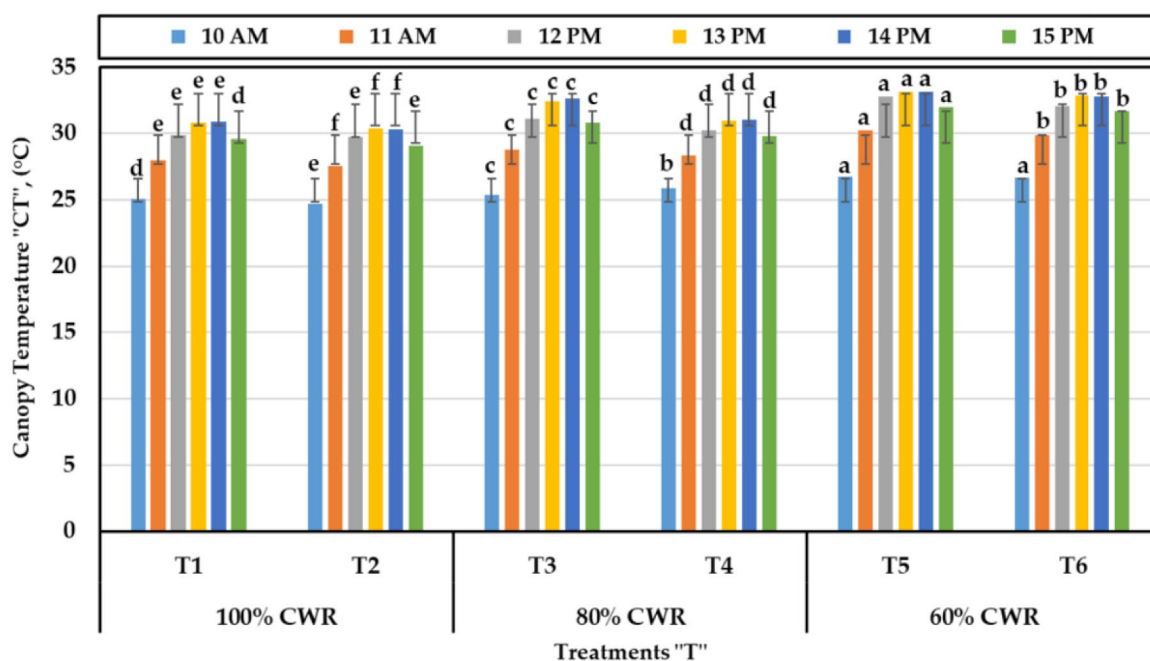
CT: Canopy temperature, T: Treatment, CWR: Crop water requirements.

Fig. 7 Comparison of average plant canopy temperature, expressed, under different applied irrigation water for (SDI). and (SSDI) systems through the development stage. Differences between parameters marked with different letters are statistically significant at the $P < 0.05$ level



CT: Canopy temperature, T: Treatment, CWR: Crop water requirements.

Fig. 8 Comparison of average plant canopy temperature, expressed, under different applied irrigation water for (SDI). and (SSDI) systems through the mid stage. Differences between parameters marked with different letters are statistically significant at the $P < 0.05$ level



CT: Canopy temperature, T: Treatment, CWR: Crop water requirements.

Fig. 9 Comparison of average plant canopy temperature, expressed, under different applied irrigation water for (SDI). and (SSDI) systems through the late stage. Differences between parameters marked with different letters are statistically significant at the $P < 0.05$ level

Figure 7 shows that differences in the applied irrigation water resulted in variations in the measured canopy temperature over time. The lowest measured canopy temperatures of 21.24, 21.39, 21.92, 22.00, 23.43, and 23.43 °C were observed under treatments T2, T1, T4, T3, T6, and T5, respectively, at 10 AM. The highest measured canopy temperatures of 24.44, 24.45, 24.66, 25.88, 26.55, and 27.16 °C were observed under treatments T2, T1, T4, T3, T6, and T5, respectively, at 2 PM. The mean air temperature in the greenhouse was recorded as 22.18 °C at 10 AM and 26.34 °C at 2 PM, while the mean relative humidity (RH) was 53.04 % at 10 AM and 42.89 % at 2 PM.

Differences in the applied irrigation water also resulted in variations in mean canopy temperatures recorded during the development stage. The lowest mean canopy temperature of 23.48 °C was observed under the subsurface drip irrigation treatment with 100 % of the water requirement (T2), while the highest mean canopy temperature of 25.93 °C was observed under the surface drip irrigation treatment with 60 % of the water requirement (T5). The mean air temperature in the greenhouse was recorded as 25.09 °C.

Figure 8 shows that differences in applied irrigation water resulted in variations in the measured canopy temperature over time. The lowest measured canopy temperatures of 18.77, 19.35, 19.38, 19.87, 20.11, and 21.13 °C were observed under treatments T2, T1, T4, T3, T6, and T5, respectively, at 10 AM. The highest measured canopy temperatures of 24.77, 24.89, 25.11, 25.87, 27.35, and 27.41 °C were observed under treatments T2, T1, T4, T3, T6, and T5, respectively, at 2 PM. The mean air temperature in the greenhouse was recorded as 18.86 °C at 10 AM and 27.30 °C at 2 PM, while the mean relative humidity (RH) was 71.38 % at 10 AM and 59.44 % at 2 PM.

Differences in the applied irrigation water also led to variations in the mean canopy temperatures recorded during the mid-stage. The lowest mean canopy temperature of 22.95 °C was observed under the subsurface drip irrigation treatment with 100 % of the water requirement (T2), while the highest mean canopy temperature of 25.49 °C was observed under the surface drip irrigation treatment with 60 % of the water requirement (T5). The mean air temperature in the greenhouse was recorded as 24.85 °C.

Figure 9 shows that differences in applied irrigation water resulted in variations in the measured canopy temperature over time. The lowest measured canopy temperatures of 24.67, 25.05, 25.87, 25.38, 26.64, and 26.74 °C were observed under treatments T2, T1, T4, T3, T6, and T5, respectively, at 10 AM. The highest measured canopy temperatures of 30.29, 30.91, 31.04, 32.61, 32.81, and 32.81 °C were observed under treatments T2, T1, T4, T3, T6, and T5, respectively, at 2 PM. The mean air temperature in the greenhouse was recorded as 25.55 °C at 10 AM and 32.67 °C

at 2 PM, while the mean relative humidity (RH) was 51.06 % at 10 AM and 38.82 % at 2 PM.

Differences in the applied irrigation water also led to variations in the mean canopy temperatures recorded during the late stage. The lowest mean canopy temperature of 28.62 °C was observed under the subsurface drip irrigation treatment with 100 % of the water requirement (T2), while the highest mean canopy temperature of 31.35 °C was observed under the surface drip irrigation treatment with 60 % of the water requirement (T5). The mean air temperature in the greenhouse was recorded as 30.60 °C.

The statical analysis results revealed that T5 (60% of CWR) has the highest canopy temperature consistently and is significantly different from all other treatments at all points of the time. T6 (60% of CWR) has an average temperature that varies significantly from T5, T3, T4, T1, and T2. T3 (80% of CWR) overlaps with T6 at times (12:00 PM, 1:00 PM, 3:00 PM) but is generally lower than T5 and T6. T4, T1, and T2 (80% and 100% of CWR) have the lowest canopy temperatures and do not vary significantly from each other at most times.

3.3 Actual yield produced (Y)

The data presented in Table 2 indicate that subsurface drip irrigation (SSDI) produced higher green bean yields than surface drip irrigation (SDI). The average yields showed a statistically significant difference, with SDI yielding 26.844 t ha⁻¹ and SSDI yielding 30.156 t ha⁻¹. Clear distinctions were observed between treatments under both irrigation systems. Under SDI, total green bean yield varied significantly among treatments T1, T3, and T5, with yields of 25.425, 28.719, and 26.390 t ha⁻¹, respectively. Under SSDI, treatments T2, T4, and T6 yielded 24.390, 33.614, and 32.466 t ha⁻¹, respectively. The highest yields

Table 2 The actual yield produced (Y) of green bean under different applied irrigation water and irrigation system

Water applied	100 of CWR*	80 % of CWR	60 % of CWR	Average
SDI treatments	T1	T3	T5	26.844
Y (t ha ⁻¹)	25.425e**	28.719c	26.390d	
SSDI treatments	T2	T4	T6	30.156
Y (t ha ⁻¹)	24.390f	33.614a	32.466b	

*CWR Crop water requirements; T Treatment; SDI Surface drip irrigation; SSDI Subsurface drip irrigation; and Y: Actual yield produced. ** Different letters indicate significant differences between means at a given confidence level ($p < 0.05$) according to Tukey's HSD test. The same letters mean no significant difference between those treatments

28.719 t ha⁻¹ (SDI) and 33.614 tons t ha⁻¹ (SSDI) were recorded under treatments T3 and T4, both of which received 80% of the crop evapotranspiration (ET_c) irrigation requirement. This outcome can be attributed to differences in water application. Treatments receiving 100% ET_c had the highest water input, while those at 60% ET_c received the lowest. Notably, the greatest yield increases (32.2% and 27.7%) were observed in treatments T4 and T6, respectively, while the lowest yield occurred under T2 (100% ET_c), likely due to over-irrigation.

Statistical analysis confirmed significant differences in green bean yield based on both the irrigation system and water treatment. The highest yield (33.61 t ha⁻¹) was achieved using SSDI combined with 80% of the water requirement. In contrast, the lowest yield (24.39 t ha⁻¹) also occurred under SSDI but with full (100%) water application. Moreover, the interaction between the irrigation system and water treatment had a significant effect on yield, with the SSDI + 80% ET_c combination producing the highest performance.

3.4 Water productivity (WP)

Table 3 clearly illustrates the interaction between irrigation method (SDI and SSDI) and irrigation water level (100, 80, and 60 %) in green bean cultivation. The volume of irrigation water applied varied with both the irrigation system and water level, with the highest amount (3185 m³ha⁻¹) applied under full irrigation (100 % ET_c), and the lowest (2065 m³ha⁻¹) under deficit irrigation (60% ET_c). Water productivity (WP) values also differed significantly among treatments, ranging from 7.66 kg m⁻³ to 15.73

kg m⁻³. The highest WP (15.73 kg m⁻³) was achieved under SSDI with the lowest water level (T6, 60% ET_c), while the lowest efficiency (7.66 kg m⁻³) was observed under SSDI at full irrigation (T2, 100% ET_c). Overall, the results indicate that reducing irrigation water levels tends to enhance water use efficiency, suggesting that deficit irrigation practices can be effective in improving WP in green bean production.

4 Discussion

The findings clearly indicate that, across all irrigation treatments, notable differences were observed in the vapor pressure deficit (VPD) between plots irrigated using sub-surface drip irrigation (SSDI) and those using surface drip irrigation (SDI) throughout the various crop growth stages. In particular, SSDI consistently resulted in lower VPD values compared to SDI at each developmental stage. This trend can be attributed to the inherent design of the SSDI system, which delivers water directly to the root zone below the soil surface, thereby minimizing water loss through surface evaporation. As a result, SSDI helps maintain higher soil moisture levels in the root zone, which in turn contributes to lower atmospheric demand around the plant canopy, reflected in reduced VPD values.

The vapor pressure deficit (VPD) is a critical physiological indicator of plant water stress, reflecting the difference between the moisture content of the air and the saturation point. It signals stress in two primary ways either through excessive transpiration under high VPD conditions or through impaired transpiration under very low VPD. When VPD levels are elevated, typically due to low relative humidity, the rate of water loss from leaf surfaces surpasses the rate at which roots can absorb and transport water. This imbalance prompts the plant to close its stomata to conserve water. However, stomatal closure also restricts carbon dioxide uptake, thereby reducing or halting photosynthesis. Additionally, with the stomata closed, the plant's natural mechanism for evaporative cooling is suppressed, increasing the risk of thermal damage to leaf tissues under high temperatures.

Water availability significantly influences VPD values. Studies by Muroyiwa et al. (2023), Carr (2013), and Erdem et al. (2010) have demonstrated that deficit irrigation strategies, specifically treatments supplying only 50% or 60% of the crop's water requirements, can lead to notable increases in VPD, reaching values as high as 4.92 kPa. These elevated levels are closely associated with stress responses and impaired physiological function. Moreover, it has been observed that plant growth tends to decline sharply when VPD values fall within the range of

Table 3 Water productivity (WP) with different applied irrigation water and irrigation system

Water applied	100 of CWR*	80 % of CWR	60 % of CWR
SDI treatments	T1	T3	T5
TWA (m ³ ha ⁻¹)	3185a**	2625b	2065c
Y (t ha ⁻¹)	25.425e	28.719c	26.390d
WP (kg m ⁻³)	7.98d	10.94c	12.78b
SSDI treatments	T2	T4	T6
TWA (m ³ ha ⁻¹)	3185a	2625b	2065c
Y (t ha ⁻¹)	24.390f	33.614a	32.466b
WP (kg m ⁻³)	7.66e	12.81b	15.73a

*CWR CROP water requirements; T Treatment; SDI Surface drip irrigation; SSDI Subsurface drip irrigation; TWA Total water applied; WP Water productivity; and Y: Actual yield produced. ** Different letters indicate significant differences between means at a given confidence level ($p < 0.05$) according to Tukey's HSD test. The same letters mean no significant difference between those treatments

3 to 7 kPa, further underscoring the sensitivity of crops to vapor pressure conditions under limited water availability.

Subsurface drip irrigation minimizes the vapor pressure deficit. Under full irrigation (100 % ET_C), the vapor pressure deficit was lower than under deficit treatments for both irrigation systems. Vapor pressure deficit data help explain the water stress among different treatments. In treatments T1 and T2, the vapor pressure deficit remained lower than all treatments throughout the entire growth cycle. In contrast, under treatments T3 and T4, the vapor pressure deficit stayed in the middle between 100 % and 60 % treatments for the entire growth cycle. For treatments T5 and T6, the vapor pressure deficit remained the highest among all treatments, indicating water stress. These results are consistent with those of Muroyiwa et al. (2023) and Koehler et al. (2023).

The study revealed that variations in irrigation water levels had a noticeable impact on plant canopy temperature under both surface drip irrigation (SDI) and subsurface drip irrigation (SSDI) systems. Among the different treatments, the most pronounced increase in canopy temperature was recorded in the plots that received only 60% of the crop water requirement. In contrast, plants irrigated at 100% of the water requirement maintained significantly lower canopy temperatures, indicating better hydration and thermal regulation. The integration of an Internet of Things (IoT) monitoring system enabled continuous, real-time tracking of canopy temperature across various growth stages, offering valuable insights into crop response under varying irrigation regimes. These findings are consistent with previous studies by Jiménez et al. (2024) and Erdem et al. (2010), which also reported a strong relationship between water stress and elevated canopy temperatures.

The findings also reveal that subsurface drip irrigation (SSDI) increases average actual yield produced of green bean by about 11% compared to surface drip irrigation (SDI) in both full and deficit irrigation treatments. This improvement in actual yield produced is likely due to the higher soil water content maintained under SSDI compared to SDI. These results are consistent with findings from other studies on surface and subsurface drip irrigation systems (Al-Mansor et al. 2015; del Amor and del Amor 2007; Machado et al. 2003).

The total volume of irrigation water applied was identical for both the surface drip irrigation (SDI) and subsurface drip irrigation (SSDI) treatments. However, water savings in green bean cultivation can be effectively achieved by improving irrigation efficiency rather than simply reducing water input. Based on the results, applying irrigation water at 80% of the crop evapotranspiration (ET_C) is recommended, as it maintains an acceptable yield while minimizing water losses. This approach not only conserves water but also sustains crop productivity. These findings are consistent with earlier studies by Al-Mansor

(2015), del Amor and del Amor (2007), and Machado et al. (2003), which emphasized the importance of optimizing irrigation levels to balance yield and resource use. Moreover, the water conserved through this strategy can be allocated to irrigate additional cultivated areas, thereby enhancing the overall water use efficiency and potentially increasing total green bean production.

5 Conclusions

In conclusion, creating an effective irrigation management plan requires an understanding of the connections between crop development, actual yield produced response to different irrigation treatments, and eco-physiological characteristics. This study leveraged IoT technology to remotely control the irrigation system and continuously monitor crucial agricultural parameters, including soil moisture, canopy temperature, and vapor pressure deficit (VPD). This open-source, low-cost technology provided valuable insights for improving local decision-making and optimizing water usage.

The findings demonstrated that VPD and canopy temperature were influenced by both SDI and SSDI treatments at various stages of crop development. Lower VPD and canopy temperatures were consistently observed under SSDI treatments, indicating reduced plant stress and improved water management. Moreover, the highest actual yield produced of green bean (33.614 t ha^{-1}) and the best IWUE were achieved under SSDI treatments, particularly at 80 % of CWR.

Overall, the most effective irrigation strategy was SSDI with reduced water levels (60 % of CWR), which resulted in the highest IWUE (15.73 kg m^{-3}). This study emphasizes the potential of precision irrigation, driven by IoT technology, to enhance crop productivity, conserve water, and optimize irrigation practices in modern agriculture.

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Data availability All data supporting the results of this study are included within the article.

Declarations

Ethics approval This study did not require ethical approval.

Competing interests The authors declare no known financial or personal conflicts of interest that could have influenced the findings presented in this paper.

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