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RESEARCH ARTICLE

An IoT based efficient water management system for smart irrigation to enhance the maize crop productivity

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Abstract

Agriculture contributes a major share to the Indian economy and most of its people are dependent on it for their livelihood. This makes water an important resource that must be preserved using the latest available technologies. An adequate amount of water for irrigation is needed for healthy crops and to increase productivity. Water scarcity is a major problem facing the world, where agriculture consumes a significant portion of freshwater. Many researchers have focused on developing intelligent irrigation systems using Internet of Things (IoT) technology. This paper presents an IoT-based, cost-effective intelligent water management system for smart irrigation. The developed system uses soil moisture and weather data to take intelligent decisions to automate irrigation using a cloud-, web- and mobile-based applications. The proposed system uses eight treatments with four types of irrigation methods such as IoT-based drip irrigation (60 % and 80 % depletion levels - T1 and T2); drip irrigation based on PE ratio (60 % and 80 % depletion levels - T3, T4 and normal practice T5); surface irrigation based on IW/CPE ratio (60 % and 80 % depletion levels - T6, T7) and flood irrigation (T8) are used. In all systems, water was applied at 60 % and 80 % depletion levels. This demonstrates the IoT- and cloud-based system enable precision agriculture by reducing human intervention in irrigation. The highest water saving was recorded in IoT-based drip irrigation at 60 % depletion level (46.88 %), followed by IoT-based drip irrigation at 80 % depletion level (40.63 %). Therefore, the proposed IoT-based drip irrigation system at 60 % depletion level can be recommended for hybrid maize to achieve higher grain and straw yields.

Keywords: cloud computing; internet of things; irrigation; smart agriculture

Introduction

Agriculture is the largest consumer of freshwater in the world, accounting for up to 70 % of the total use, which makes the case for smart water management to guarantee water and food security to the world's population (1). Irrigation systems and field application methods are crucial for sustainable crop production. To avoid loss of productivity caused by water stress, farmers often apply more water than needed and as a result, not only is productivity affected, but water and energy are also wasted. Precision irrigation, on the other hand, allows water to be used more efficiently and effectively, avoiding both under- and over-watering. The smart management of water for precision irrigation in agriculture is essential for increasing crop yield and decreasing costs, while at the same time contributing to environmental sustainability.

The IoT has emerged as the natural choice for smart water management applications, even though the integration of different technologies required to make it work seamlessly in practice is still not fully accomplished (2). The emergence of IoT is a phenomenon that results from the conjunction of several factors, such as inexpensive devices, low-power wireless technologies, the availability of cloud data centers for storage and processing, management frameworks for dealing with unstructured data from social networks, high-performance computing resources in commodity platforms and computational intelligence algorithms to deal with this monumental amount of data (big data analytics).

The main objective of the research is to reduce the amount of water used in irrigation and to maximize yield per unit of water. The agricultural sector has evolved significantly to meet the needs of a growing world population, tackle sustainability issues and adjust to shifting climate conditions (3). These continuous changes underscore agriculture's resilience and enduring significance in today's landscape (4). Furthermore, agriculture plays a critical role in meeting the demands of a growing population. Projections suggest that food production needs to increase substantially by 2050 (5). Therefore, adopting technologies and enhancing crop management practices are vital to boost productivity. IoT technology combines the power of the internet with existing assets to enable remote supervision and control of devices and systems (6). This monitoring is made possible by utilizing communication technologies tailored to meet the requirements of a modern farm's infrastructure (7). These technologies encompass Bluetooth, ZigBee, Message Queuing Telemetry Transport (MQTT), Long Range (LoRa), Wi-Fi, General Packet Radio Service (GPRS) and 4G and 5G for high-speed data transfer. This connectivity fosters interaction and data exchange among devices leading to improved efficiency and accuracy in activities, through real-time data gathering, analysis and implementation (8).

A smart water management system prototype named AGRI2L was developed; AGRI2L puts forward a design to implement a low-cost smart water level and leakage monitoring system that relies on real-time data (9). Such a system makes the water resources management processes more accurate and effective. An evapotranspiration (ETo) model to accurately define plants' water requirements and enhance managing limited water resources in arid regions using neural computing has been proposed (10). Subsequently, the best practices to reduce water loss caused by traditional irrigation methods were identified. A brief and clear description of the purpose of the investigation, relating to previous research and essential arguments, should be provided (11).

Materials and Methods

A field experiment was carried out at the research farm of the Agricultural College and Research Institute, Madurai. The farm is situated in the southern agro-climate zone of Tamil Nadu.

Experimental design and treatment details

The experiment was laid out in a randomized block design with eight treatments and three replications. The test crop used was maize hybrid COH (M) 8, spaced at 60 × 25 cm.

The treatment details are as follows:

T1: IoT based drip irrigation at 60 % depletion level

T2: IoT based drip irrigation at 80 % depletion level

T3: Drip irrigation at 60 % PE

T4: Drip irrigation at 80 % PE

T5: Drip irrigation as normal practice

T6: Surface irrigation at 0.6 IW/CPE ratio

T7: Surface irrigation at 0.8 IW/ CPE ratio

T8: Flood irrigation as farmer's practice

Soil characteristics

The experiment field soil was sandy clay loam in texture. The soil samples were collected randomly from five different places in the field at a depth of 0-15 cm. The soil characteristics are mentioned in Table 1.

Crop management

All the cultural practices for maize cultivation other than treatments were followed as per the recommendation of the Crop Management Guide (2020) of Tamil Nadu Agricultural University.

Preparation of the seedbed included ploughing with disk plough, cultivator and rotavator. The formation of ridges and furrows help in saving of irrigation water in maize. The spacing of maize is 60 × 25 cm. Each treatment had 5 rows of maize. Each lateral was 26 m long and the distance between laterals was 120 cm.

Land preparation and manuring

Well-prepared ridges and furrows, which were formed after 4-5 deep ploughings, provided ideal conditions for sowing the crop. Before sowing, urea was applied based on the soil test recommendations of crop management guide (2020) is 135:62.5:50 NPK kg ha^{-1}. Urea was applied in 3 splits, mainly at the sowing, knee -high and tasseling stages. The entire dose of P and K_2O with 45 kg urea was applied at the time of sowing.

To prevent the spread of weeds, the herbicide Atrazine (500 g ha^{-1}) was applied as a pre-emergence at 3 days after sowing. The insecticide Coragen was applied at a rate of 900 mL ha^{-1} to control maize pests.

Architecture of the proposed system

The design and implementation of the IoT-based smart intelligent system were divided into two parts, namely the design of the central controller and the selection of the network operators and sensors. Implementation of this project in the field involved using the soil moisture sensor (Irrometer 200SS Watermark), solenoid valves used for actuating the relay module and pump for automatic irrigation and a water flow sensor to measure the amount of water. An operator was also used to interrupt or connect the water flow.

The block diagram of the IoT-based smart water management system and IoT-based smart irrigation unit is shown in Fig. 1 & 2. The controller unit consists of a voltage converter, motor drive module, Arduino nano microcontroller, power and GSM module. The specifications and description of the hardware inside the data acquisition system are presented in Table 2. The control box was kept inside a metal casing to protect it from rain and any other mishandling.

The control box has three option buttons–one for power off/on, second for operation mode (manual, automatic and reset) and a third for displaying the water flow status and sensor values on an LCD panel. The whole system was powered with 230 V three-phase connection. The system was programmed to open and close the solenoid volve based on the sensor values (60 % and 80 % depletion levels) for T1 and T2, pan evaporation values for T3 and

Table 1. Physical properties of initial soil samples

Available nutrients	kg ha^{-1}	Physicochemical properties*	
Nitrogen	285	pH	6.81
Phosphorus	15.2	Field capacity (%)	25.89
Potassium	418	Permanent wilting point (%)	19.72
Soil texture	Sandy clay loam	Bulk density (Mg m^{-3})	1.4
Electrical conductivity (%)	0.78	Basic infiltration rate	6mm/h
Organic carbon (%)	0.61		

*Mean of three soil samples initial soil data.

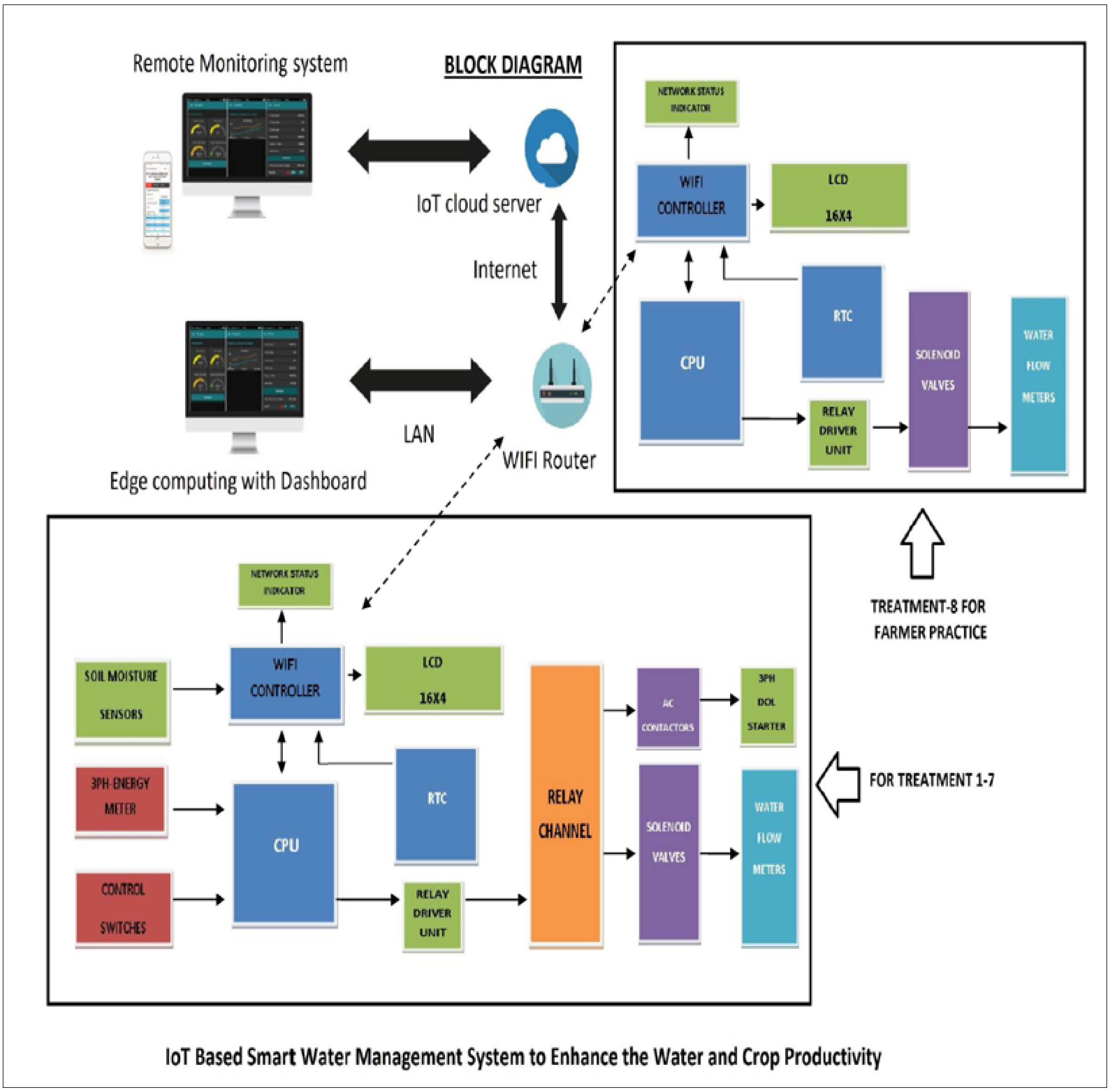

Fig. 1. IoT based smart water management system.

Fig. 2. IoT based smart irrigation unit.

Table 2. Data acquisition system hardware components

S. No	Sensor module	Function
1.	ESP -32 microcontroller	To process sensor data
2.	ESP8266 Wi-Fi module	Send the data recorded by the sensor to an IoT platform
3.	Solenoid valve	For actuating the relay module and pump for automatic irrigation
4.	Power module	To provide 3 Phase power connection
5.	Arduino nano	To control solenoid volve opening and closing based on moisture data
6.	Motor drive	To operate motor
7.	Display module	To display the data

T4 and IW/CPE ratio for treatments T6 and T7. Manual operation was followed for T5 and T8.

Software component

The software used in the study for automation IoT-Agro unit was customized according to our research needs. It consists of web- and mobile-based interface, allowing users to access the system from anywhere. The data flow diagram for the software system is shown in Fig. 3.

In the experiment field, soil moisture sensors were tested and installed. Sensors were placed in sensitive and representative locations within the crop's root zone. Soil moisture varies in three dimensions-variability in soil wetting from irrigation or rainfall, drying of soil from evaporation and root-zone water extraction for plant transpiration. Interactions among these dimensions were critical for soil proper sensor installation. The soil moisture sensors were placed at both the top and bottom of the active root system, relative to drippers. The optimal sensor position was 11 cm away from the drip line and 20 cm beneath the soil surface.

The soil moisture sensors were installed at a depth of 20 cm to help control irrigation based on soil moisture content. This device uses IoT technology to automate irrigation without human intervention. The soil moisture sensor sends signals to the ESP32's configured Wi-Fi module, which triggers the water pump and irrigates the field via a smartphone or computer application if the moisture level falls below the predefined threshold.

The measured variables were continuously and automatically recorded and sent to the cloud-based server. The developed data acquisition system was switched on and installed in the agriculture field (Fig. 4). The IoT device is directly linked to the IoT analytics platform web service to access and analyse live data in the cloud. The field channel valves for each treatment were also controlled accordingly.

Irrigation

Irrigation scheduling refers to determining when and how much water to apply to the field and thus has a direct effect on water use efficiency (WUE). The quantity of water to be applied is estimated

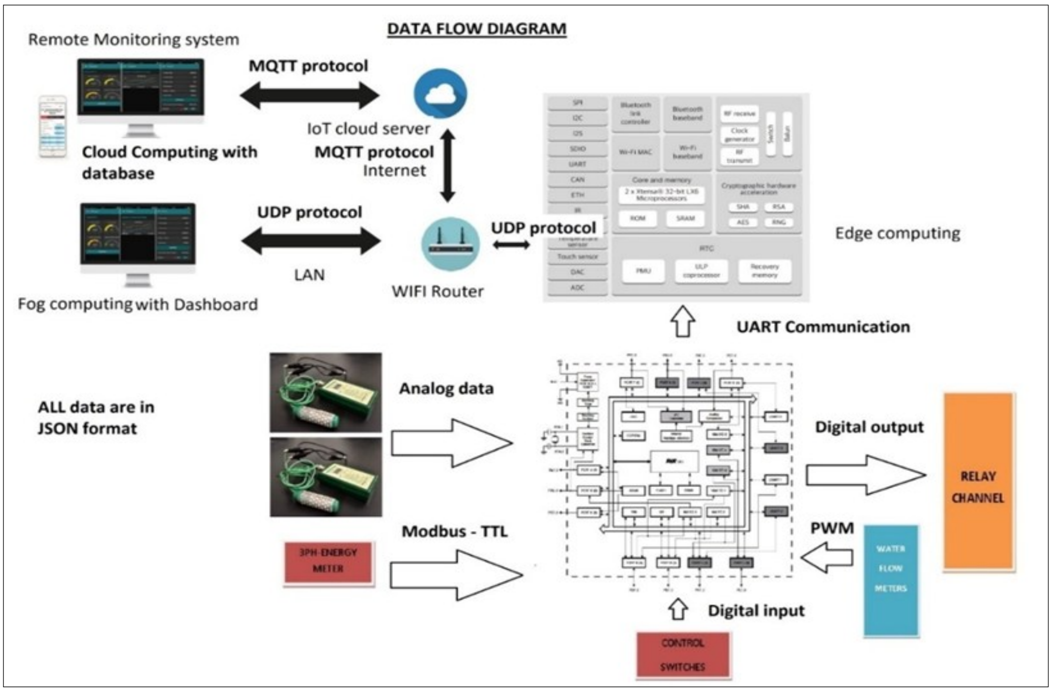

Fig. 3. IoT based smart irrigation data flow diagram.

Fig. 4. Experiment field at AC & RI, Madurai.

using a set of criteria to determine the irrigation requirement and a strategy to prescribe how much to apply. Efficient application of irrigation water requires an understanding of dynamic plant-water use, which has a relationship with weather, soil characteristics and plant physiology. Efficient irrigation scheduling applies irrigation water at the right time and in the right quantity to optimize production and mitigate adverse environmental impacts. On the other hand, poor irrigation scheduling results in under-watering or waterlogging, which affects WUE. In this experiment, four types of irrigation methods are applied: IoT based drip irrigation, drip irrigation based on PE ratio, surface irrigation based on IW/CPE ratio and flood irrigation.

Sensor-based irrigation

The irrigation timing in the smart farm was determined by soil moisture depletion from field capacity using a moisture sensor installed in the field. Two sensors were installed in the field to measure the soil moisture values. The optimal sensor depth of the maize crop was 20 cm. The sensors were connected to the controller through wired connections for better accuracy. The flow of water to the field was controlled by the soil moisture values received from the treatments (T1 and T2). The valves automatically opened and closed based on predefined soil moisture sensor readings for real-time operation.

Accordingly, the plants were irrigated from planting until corolla emergence, milking stage and moisture drainage and from seed milking to physiological maturity based on 60 % of field capacity moisture drainage (T1) and 80 % of field capacity moisture drainage (T2). The input parameter for the minimum (60 % of FC for T1 and 80 % of FC for T2) and maximum (100 % FC) threshold values of soil moisture need to be set for automatic irrigation operation for T1 and T2. Users can set the value according to the crop-water requirement and management-allowed deficit for a specific crop. As the soil moisture reaches or falls below a pre-set threshold value, the motor driver module activates and opens the solenoid valve. Similarly, when the soil moisture reaches 100 % of field capacity, the motor driver module is activated and closes the solenoid volve.

T1: IoT based drip irrigation at 60 % depletion level

1. Read soil moisture sensor value and assign the value to the variable "sval".

   //sensor value assigned to the "sval" variable.

2. Assign field capacity (100 %) as 25.89.
3. If sval ≥ 25.89 then no need to irrigate (Already 100 % soil moisture available).
4. If sval = 15.5 (60 % of field capacity):

a. Start irrigation (send a signal to open the 1st valve).

b. Measure the water content and store the data and quantity of water applied in the field.

c. Continuously monitor the soil moisture value.

d. Stop the irrigation when the soil moisture value reaches 25.89.

T2: IoT based drip irrigation at 80 % depletion level

1. Read soil moisture sensor value and assign the value to the variable "sval".
2. Assign field capacity (100 %) as 25.89.
3. If sval ≥ 25.89 then there is no need to irrigate (already 100 % soil moisture available).
4. If sval = 20.71 (80 % of field capacity):

a. Start irrigation (send a signal to open the 1st valve).

b. Measure the water content and store the data and quantity of water applied in the field.

c. Continuously monitor the soil moisture value.

d. Stop the irrigation when the soil moisture value reaches 25.89

Weather-based monitoring

Weather-based monitoring involves real-time estimation of reference evapotranspiration (ET_0) using measured weather parameters and thus indicates the water lost by the plants and the soil environment. The quantity of water lost through ET_0 depends on humidity, wind speed, solar radiation and air temperature. The temporal dynamics of evapotranspiration on daily timescales are appropriate for determining crop water use in Treatment T3 and T4.

The algorithm for Treatment T3, T4 and T5 is as follows:

T3: Drip irrigation at 60 % PE

1. Accept PAN evaporation value (PE_1, PE_2, PE_3) every three days.
2. Calculate water irrigation requirement: $X = ((PE_1, PE_2, PE_3) \times 0.60)$.
3. Send the signal to open the valve and Irrigate X mm of water in the field
4. Measure the water content and store the data and quantity of water applied in the field.

T4: Drip irrigation at 80 % PE

1. Accept PAN evaporation value (PE_1, PE_2, PE_3) every three days.
2. Calculate water irrigation requirement: $X = ((PE_1, PE_2, PE_3) \times 0.80)$.
3. Send the signal to open the valve and Irrigate X mm of water in the field
4. Measure the water content and store the data and quantity of water applied in the field.

T5: Drip irrigation at normal practice

Send the signal to open the valve for every three days and irrigate required quantity of water in the field.

Measure the water content and store the data and quantity of water applied in the field.

Surface irrigation

T6: Surface irrigation at 0.6 IW/CPE ratio

Accept PAN evaporation value (PE total = PE_1, PE_2, PE_3,..) continuously until it reaches 83.3 mm.

If PE total = 83.3 mm

Send the signal to open the valve and irrigate 50 mm of water in the field.

Measure the water content and store the data and quantity of water applied in the field.

T7: Surface irrigation at 0.8 IW/ CPE ratio

Accept PAN evaporation value (PE total = PE_1, PE_2, PE_3,..) continuously until it reaches 62.5 mm.

If PE total = 62.5 mm

Send the signal to open the valve and irrigate 50 mm of water in the field.

Measure the water content and store the data and quantity of water applied in the field.

T8: Farmer practice

Send the signal to open the valve every three days and irrigate the required quantity of water in the field

Measure the water content and store the data and quantity of water applied in the field.

Drip irrigation water delivery system was used for treatments T1 to T5, providing the ability to deliver water directly to the root zone in accurate amounts based on the plant's current needs. Drip irrigation is the only irrigation technique capable of avoiding water stress without over-watering. In the sensor-based system (T1 and T2), irrigation was based on intelligent sensor-based control, Pan evaporation-based irrigation was applied in drip irrigation treatments (T3, T4 and T5). Irrigation was applied to the treatments (T6 and T7) using IW/CPE ratio. The irrigation for T3 to T7 was scheduled using the daily water sheet balance method. Flood irrigation was applied based on farmer practice at three-day intervals.

Harvesting and threshing

Maize is ready for harvesting when the stalks and leaves are somewhat green, but the husk cover has dried and turned brown. Maize was shelled when the moisture content ranged between 15 % - 20 %. A manual method was used for threshing maize with husk. The maize cobs were dried for 3-4 days after harvesting to improve grain recovery and reduce breakage losses during shelling.

Biometric observations

Five plants were selected randomly and tagged for recording biometric observations in each experimental plot. Growth parameters were recorded at 45 days after sowing (DAS), 60 DAS and at harvest. Yield attributes, grain and straw yields, as well as water use and water saving, were recorded at harvest.

Growth parameters

Plant height

Plant height was measured from the base of plant to the tip of the topmost leaf at 30 DAS, 60 DAS and harvest in all the sample plants. Mean values were recorded and expressed in centimetres (cm).

Leaf area index (LAI)

Leaf area index was calculated at 30 DAS, 60 DAS and at harvest in all the sample plants. The total number of green leaves, length and breadth of third leaf from the top in the sample plants were recorded in each plot. LAI was worked out using the given formula (12).

LAI = L × B × K × Number of green leaves / spacing (cm)

Where,

L - Length of the 3rd leaf in cm

B - Width of the 3rd leaf in cm

K - Constant factor (0.75)

Dry matter production (DMP)

The samples were collected along the roots from all treatments at 30 DAS, 60 DAS and at harvest stage. The samples were initially shade-dried followed by hot air oven drying at 60 °C until they reached a constant weight. The roots were separated and the dry weight of shoot and roots were calculated, from which dry matter production per hectare was determined and expressed in kg ha^{-1}.

Yield attributes and yield

Grain yield

The manually harvested crop from each net plot was threshed and cleaned separately. The maize ears were dried for 3-4 days after harvesting and then weighed. The grain yield was expressed in kg ha^{-1}.

Straw yield

The straw collected from each plot was dried for two consecutive days and weighed separately. The straw yield was expressed in kg ha^{-1}.

Water use studies

Total water use

Total water use was calculated as the sum of irrigation water applied and effective rainfall. Effective rainfall was computed by water balance method using rainfall data, data pan evaporation, Kc value and maximum water-holding capacity of soil.

Water use efficiency (WUE)

WUE is the amount of yield that can be produced from a given quantity of water. WUE was worked out using the following formula expressed in kg ha^{-1} mm^{-1}.

WUE = grain yield kg ha^{-1} / Total water use (mm)

Statistical analysis

The data acquired throughout the investigation were statistically analysed (13). When the critical difference was calculated at a 5 % confidence level, variations among treatments were considered significant.

Results and Discussion

Growth analysis elucidated the impact of sensor-based irrigation levels on all growth-attributing parameters. Plant height is a direct index for measuring the growth and vigor of the plant. The data pertaining to plant height of maize, as influenced by irrigation methods and irrigation schedules (Table 3). Perusal of the data indicates that the plant height of maize progressively increased with the advancement of crop age up to harvest, irrespective of the treatments. The plant height of maize was significantly influenced by irrigation methods and irrigation levels.

Favorable soil-plant-water balance under sensor-based irrigation treatments (T1 to T2) might have stimulated increased meristematic cell activity and internodal cell elongation, resulting in a higher growth rate, which in turn promoted greater plant height in maize compared to flood irrigation. Among irrigation methods, significantly higher plant height was recorded at 30 DAS, 60 DAS and at harvest (83.40, 204.00 and 217.3 cm) in IoT sensor-based drip irrigation at 60 % depletion level over flood irrigation method (67.53, 160.73 and 172.00 cm, respectively).

Within drip irrigation methods (T1 to T5), IoT-based drip irrigation at the 60 % depletion level (T1) recorded the highest plant height (217.33 cm), followed by IoT-based drip irrigation at 80 % depletion (T2), which recorded a plant height (200.33 cm) and drip irrigation at 80 % PE (T4), which recorded 191.93 cm.

Table 3. Influence of irrigation methods and level on plat height (cm) of hybrid maize

Treatments	45 DAS	60 DAS	At harvest
T_1: IoT based drip irrigation at 60 % depletion level	83.40	204.00	217.33
T_2: IoT based drip irrigation at 80 % depletion level	82.03	185.10	200.33
T_3: Drip irrigation at 60 % PE	81.70	179.40	190.68
T_4: Drip irrigation at 80 % PE	81.97	179.93	191.93
T_5: Drip irrigation as normal practice	81.13	179.03	189.23
T_6: Surface irrigation at 0.6 IW/CPE ratio	77.37	163.43	173.83
T_7: Surface irrigation at 0.8 IW/ CPE ratio	78.13	170.93	181.37
T_8: Flood irrigation as farmer's practice	67.53	160.73	172.00
SE±m	1.17	4.54	4.95
C.D. at 5 %	3.54	13.77	15.02

Irrigation scheduling based on soil-moisture sensors led to greatest leaf area and accumulation of fresh and dry biomass (14). This was mainly due to irrigating the crop at the required time, which resulted in the continuous availability of optimum moisture near to root zone, thereby enhancing nutrient uptake and promoting greater cell division and elongation. On the other hand, water stress under flood irrigation has reduced plant height by 20.85 %. Similar results were previously noticed (15).

Leaf area index

Irrigation methods had a significant influence on the LAI of maize. A gradual increase in LAI was observed from early to the flowering stage. The data pertaining to the LAI maize as influenced by irrigation methods and irrigation levels are presented in Table 4.

Among the Irrigation method, significantly higher LAI (5.20) was recorded at in IoT sensor-based drip irrigation at 60 % depletion level, whereas the lowest LAI (3.30) was recorded under flood irrigation method.

Within drip irrigation methods (T1 to T5), IoT-based drip irrigation at 60 % depletion level (T1) recorded the highest LAI (5.20), followed by IoT-based drip irrigation at 80 % depletion level (T2) with an LAI of 4.62 and drip irrigation at 80 % PE (4.46).

Dry matter production

The plant DMP among the treatments differed significantly (Table 5). Among the irrigation methods (T1 to T8), significantly higher DMP (18344 kg ha^{-1}) in IoT sensor-based drip irrigation at 60 % depletion level and the lowest DMP (11765 kg ha^{-1}) was recorded under surface irrigation (T8).

Within drip irrigation methods (T1 to T5), IoT-based drip irrigation at 60 % depletion level (T1) recorded the maximum DMP (18344 kg /ha), followed by (T2) IoT-based drip irrigation at 80 % depletion level (T2, 18123 kg ha^{-1}) and drip irrigation at 80 % PE (T4, 16718 kg ha^{-1}).

Yield attributes

Irrigation plays an imperative role in determining the potential of maize to produce an economic yield. Characters such as cob length, number of kernels per pod and 100 kernel weight are adversely affected by moisture stress (Table 6).

In the present study, IoT sensor-based drip irrigation at 60 % depletion level recorded longer cobs (22.7 cm) with greater girth (16.4 cm) and 100-kernel weight (27.8 g) compared to the flood irrigation method, which produced shorter cobs, (17.0 cm), smaller cob girth (13.4 cm) and 100-kernel weight (23.8 g).

Table 4. Influence of irrigation methods and level on LAI of hybrid maize

Treatment	30 DAS	60 DAS	At harvest
T_1: IoT based drip irrigation at 60 % depletion level	1.87	3.22	5.20
T_2: IoT based drip irrigation at 80 % depletion level	1.85	2.77	4.62
T_3: Drip irrigation at 60 % PE	1.31	2.04	3.99
T_4: Drip irrigation at 80 % PE	1.53	2.09	4.46
T_5: Drip irrigation as normal practice	1.43	2.26	3.64
T_6: Surface irrigation at 0.6 IW/CPE ratio	1.16	2.06	3.54
T_7: Surface irrigation at 0.8 IW/ CPE ratio	1.27	2.23	3.59
T_8: Flood irrigation as farmer's practice	1.14	2.03	3.30
SE±m	0.08	0.13	0.19
C.D. at 5 %	0.23	0.39	0.57

Table 5. Influence of irrigation methods and level on dry matter production (kg/ha) of hybrid maize

Treatment	30 DAS	60 DAS	At harvest
T_1: IoT based drip irrigation at 60 % depletion level	3305	12297	18344
T_2: IoT based drip irrigation at 80 % depletion level	3294	12208	18123
T_3: Drip irrigation at 60 % PE	3232	11603	16344
T_4: Drip irrigation at 80 % PE	3256	11865	16718
T_5: Drip irrigation as normal practice	3201	11188	15437
T_6: Surface irrigation at 0.6 IW/CPE ratio	3133	10884	13455
T_7: Surface irrigation at 0.8 IW/ CPE ratio	3107	10003	12659
T_8: Flood irrigation as farmer's practice	3155	9345	11765
SE±m	41.40	144.15	165.23
C.D. at 5 %	125.60	437.28	501.23

Table 6. Influence of irrigation methods and yield attribute of hybrid maize

Treatment	Cob length (cm)	Cob girth (cm)	100 kernel weight (g)
T_1: IoT based drip irrigation at 60 % depletion level	22.7	16.4	27.8
T_2: IoT based drip irrigation at 80 % depletion level	20.3	15.2	27.4
T_3: Drip irrigation at 60 % PE	18.7	14.2	26.8
T_4: Drip irrigation at 80 % PE	19.2	14.9	26.8
T_5: Drip irrigation as normal practice	18.5	14.1	25.6
T_6: Surface irrigation at 0.6 IW/CPE ratio	17.2	13.8	24.3
T_7: Surface irrigation at 0.8 IW/ CPE ratio	17.4	14.0	24.7
T_8: Flood irrigation as farmer's practice	17.0	13.4	23.8
SE±m	0.5	0.5	0.5
C.D. at 5 %	1.4	1.6	1.5

Among the drip irrigation methods (T1 to T5), IoT-based drip irrigation at the 60 % depletion level (T1) recorded the highest cob length (22.7 cm), cob girth (16.4 cm) and 100-kernel weight (27.8 g), followed by IoT-based drip irrigation at 80 % depletion level (T2) with cob length (20.3 cm), cob girth (15.2 cm) and 100-kernel weight (27.4 g) and drip irrigation at 80 % PE (T4) with cob length (19.2 cm), cob girth (14.9 cm) and 100-kernel weight (26.8 g).

In the present study, among the irrigation methods, IoT sensor-based drip irrigation at the 60 % depletion level (T1) recorded the maximum grain yield (7050 kg ha^{-1}) and straw yield (11069 kg ha^{-1}) and the minimum grain yield (5069 kg ha^{-1}) and straw yield (7604 kg ha^{-1}) were recorded under surface irrigation method (T8) (Table 7) (Fig. 5).

Treatment T1 was followed by IoT-based drip irrigation at 80 % depletion level (T2) and drip irrigation at 80 % PE (T4). The increase in the yield parameter was due to the continuous availability of sufficient soil moisture, which also favored photosynthetic activity and the translocation of photosynthates to the sink, thereby improved 100-seed weight. Conversely, significantly lower grain yield under surface irrigation was associated with the non-availability of adequate moisture at critical stages, leading to stress near the effective root zone.

Water use and WUE

The variation observed in irrigation frequency in maize was due to senor-based irrigation management. The data pertaining to the irrigation interval for different irrigation treatments are depicted in Fig. 6. During the study period (April to July 2023), the maximum number of irrigations (24 times) was recorded in drip irrigation as normal practice (T5), followed by drip irrigation at 60 % PE (T3) with 21 irrigations, which was on par with drip irrigation at 80 % PE (T4). The lowest irrigation frequency (6 times) was recorded in surface irrigation at 0.6 IW/CPE ratio due to higher rainfall (322.6 mm) contribution. Among the sensor-based drip irrigation treatments, irrigation frequencies of 16 times (T1) and 12 times (T2) were recorded for 60 % and 80 % depletion levels, respectively. The variation in total water usage (ha–mm) under various irrigation management practices is presented in Table 8.

Table 7. Influence of irrigation methods and irrigation levels on grain and straw yields (kg ha^{-1}) of hybrid maize

Treatment	Grain yield (kg ha^{-1})	Straw yield (kg ha^{-1})
T_1: IoT based drip irrigation at 60 % depletion level	7050	11069
T_2: IoT based drip irrigation at 80 % depletion level	6746	10557
T_3: Drip irrigation at 60 % PE	6118	9400
T_4: Drip irrigation at 80 % PE	6443	9922
T_5: Drip irrigation as normal practice	5819	8890
T_6: Surface irrigation at 0.6 IW/CPE ratio	5402	8187
T_7: Surface irrigation at 0.8 IW/ CPE ratio	5600	8425
T_8: Flood irrigation as farmer's practice	5069	7604
SE±m	64.64	82.23
C.D. at 5 %	196.08	249.46

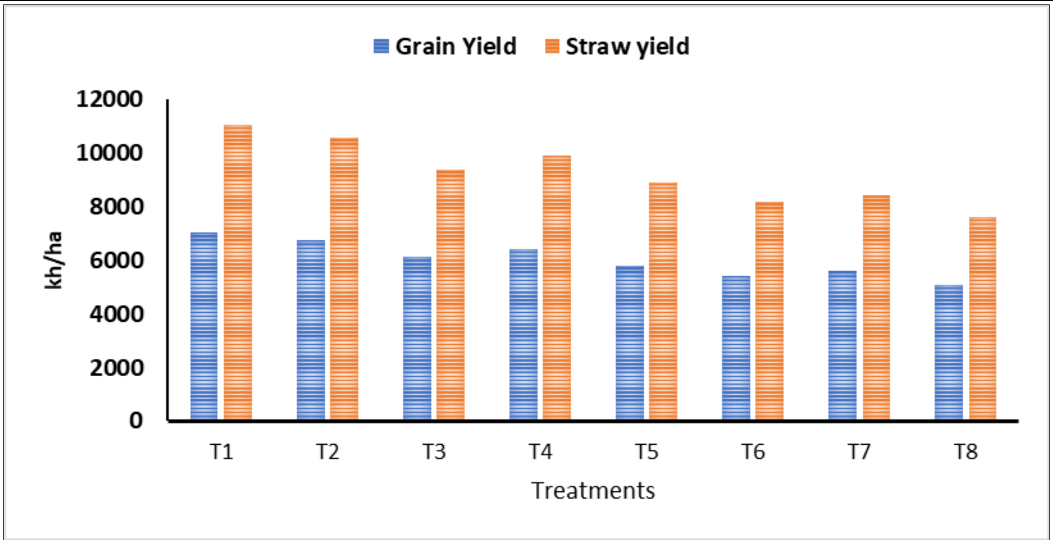

Fig. 5. Influence of irrigation methods and levels on grain and straw yields (kg ha^{-1}) of hybrid maize.

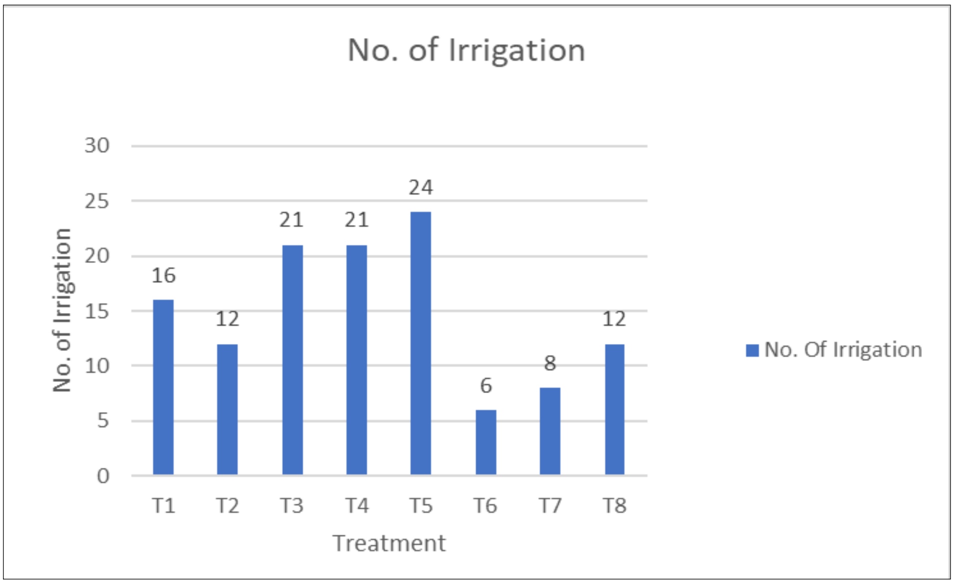

Fig. 6. Influence of irrigation methods and number of irrigations of hybrid maize.

Flood irrigation of maize used the maximum amount of water (809.69 ha-mm), followed by drip irrigation as normal practice (619.05 ha-mm), drip irrigation at 80 % PE (563.25 ha-mm), drip irrigation at 60 % PE (523.09 ha-mm), surface irrigation at 0.8 IW/ CPE ratio (554.95 ha-mm), IoT-based drip irrigation at 80 % depletion level (480.7 ha-mm) and surface irrigation at 0.6 IW/CPE ratio (504.95 ha-mm). The lowest water use (430.1 ha-mm) was recorded in IoT-based drip irrigation at 60 % depletion level.

The treatment also differed significantly for WUE under IoT sensor-based irrigation management (Table 6). Significantly higher WUE (16.39 kg ha-mm^{-1}) was recorded under IoT-based drip irrigation at 60 % depletion level, followed by IoT-based drip irrigation at 80 % depletion level (14.03 kg ha-mm^{-1}), drip irrigation at 60 % PE (11.70 kg ha-mm^{-1}) and surface irrigation at 0.6 IW/CPE ratio (10.70 kg ha-mm^{-1}). In contrast, the lowest WUE (6.26 kg ha-mm^{-1}) was observed under flood irrigation.

Higher WUE with sensor-based irrigation system was attributed to reduced water loss and efficient water utilization by the plants, resulting in higher yield. The favorable effects of sensor and drip irrigation helped in maintaining constant soil moisture potential. Conversely, the lower WUE under surface irrigation was due to greater evaporation losses of soil moisture resulting from a larger exposed wetting surface after irrigation. The highest water saving (46.88 %) was recorded under IoT-based drip irrigation at 60 % depletion level, followed by IoT-based drip irrigation at 80 % depletion level (40.63 %).

Conclusion

IoT-based drip irrigation at 60 % depletion level can be recommended for hybrid maize to enhance grain and straw yield, WUE and irrigation water savings (46.88 %). Farmers can use these IoT technologies to schedule irrigation and monitor their fields remotely from different locations. The application of artificial intelligence (AI) in agriculture is expected to bring a new revolution in efficient irrigation management and water conservation. Smart irrigation technologies are transforming modern agriculture by increasing irrigation efficiency and improving crop yields. The amount of irrigation water used in agriculture can be reduced substantially, allowing the saved water to be utilised for cultivating additional crops. Sensor-based systems help improve resource utilization and promote sustainable water management.

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Authors' contributions

PP and AV carried out the complete research work. PP prepared the manuscript. BS and PS performed the analysis. MI handled the graphical and visualization work. SPS contributed to the language editing and correction of the manuscript. All authors read and approved the final manuscript.

Table 8. Total water used and WUE of maize and water saving in maize

Treatment	Effective rainfall (mm)	Irrigation water (mm)	Total water used (mm)	WUE (kg ha-mm $^{-1}$)	Water saving (%)
T_1: IoT based drip irrigation at 60 % depletion level	209.69	220.41	430.1	16.39	46.88
T_2: IoT based drip irrigation at 80 % depletion level	209.69	271.01	480.7	14.03	40.63
T_3: Drip irrigation at 60 % PE	312.13	210.96	523.09	11.70	35.40
T_4: Drip irrigation at 80 % PE	284.65	278.60	563.25	11.44	30.44
T_5: Drip irrigation as normal practice	225.7	393.35	619.05	9.40	23.54
T_6: Surface irrigation at 0.6 IW/CPE ratio	204.95	300	504.95	10.70	37.64
T_7: Surface irrigation at 0.8 IW/ CPE ratio	154.95	400	554.95	10.09	31.46
T_8: Flood irrigation as farmer's practice	209.69	600	809.69	6.26	0

Compliance with ethical standards

Conflict of interest: There is no conflict of interest between the authors.

Ethical issues: None

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